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FORECASTING RECOVERABLE SPARES USING

BOX-JENKINS TIME SERIES TECHNIQUES

THESIS

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AFIT/GLM/LSM/89S-27

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THESIS

Presented to the Faculty of the School of

Systems and Logistics

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Requirements for the Degree of

Master of Science in Logistics Management

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Preface

The purpose of this study was to determine if Box-Jenkins time series techniques forecast C-135 aircraft recoverable spares accurately. Emphasis has been placed on finding the best methods for forecasting aircraft recoverable spares since they've been greatly underestimated in the last few years. This research consisted of developing Box-Jenkins transfer function models which used past flying hours to forecast future demand, Box-Jenkins univariate models which used past demand and its relationship over time to forecast future demand, and simple exponential smoothing models which emphasize recent demand data more heavily in forecasting future demand. All three types of models produced very accurate results when forecasting demand one quarter into the future. The simple exponential smoothing models had the most accurate results of the three for the quarter.

This thesis would not have been possible without the assistance of certain individuals. A special thanks is owed to Lieutenant Colonel Bruce Christensen whose help and guidance as my advisor was greatly appreciated. I would also like to thank Captain Terry Tong and Larry Collins for helping me obtain flying hours and demand data. Finally, a heartfelt thanks goes to my family and friends for their love and support throughout this research endeavor.

Tammy M. Haight

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Abstract

In recent years, Air Staff directed a comprehensive review of the spares forecasting process due to significant underestimates of spares requirements. The purpose of this study was to determine if time series forecasting models could accurately forecast demand for aircraft recoverable spares. Box-Jenkins time series analysis was used to analyze and develop forecasting models for ten C-135 spares.

Two different Box-Jenkins models were developed for each spare to forecast demand. These forecasts were compared to forecasts done using simple exponential smoothing and to the actual demand. The first type of Box-Jenkins model built was the multivariate (transfer function) model. In these models, flying hours are the independent/input variable and demand is the dependent/output variable for forecasting. The second model is the univariate model in which past demand relationships are used to forecast demand.

The three models forecast one quarter of demand. The results were compared to the actual demand. Results showed low correlation between flying hours and demand in the multivariate models. Though each type of model forecast well, simple exponential smoothing had better results. In the majority of forecasts, the three models overestimated demand.

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I. Introduction

General Issue

In 1982-83, the Air Force Chief of Staff ordered a comprehensive study of the aircraft recoverable spares forecasting process to analyze understated forecasts totalling millions of dollars. An aircraft recoverable spare is a part that is normally not expended in use and can be reused after recovery and repair (8:571). One of the main areas of concern for Air Staff was the requirements computation system (7:58). The requirements computation system assumed a linear causal relationship between both flying hours and demand over time. This linear regression technique known as Peacetime Operating Stock Spares Estimation (POSSEM) underestimated spares demand by more than $1.3 billion for 1983 - 1985 (10:2). Spares budget requirements for the future were determined based on the current forecast demand.

Another concern was the increased cost of weapon system spares. This concern has magnified the search for improved forecasting techniques because "reparable spares of aircraft components amounted to a computed budget requirement of $4.077 billion is FY 1985" (14:v). As costs increase, recent cuts in the Air Force budget are forcing managers to more

accurately predict future item demand for recoverable aircraft spares. Research of forecasting techniques is ongoing.

Countless manhours have been spent by the Logistics Management Institute, the Air Force Logistics Command, and the Logistics Mangement Center in researching and testing current forecasting techniques for estimating recoverable spares demand. Many researchers recommend linear regression and forecasting techniques such as exponential smoothing which stress linear relationships. Other current research has questioned the assumption that the relationship between flying hours and demand is linear. Analyzing the question of linearity between flying hours and demand is a key step in determining which forecasting techniques best predict future spares requirements.

Research Question

The current requirements computation system understates recoverable spares demand at a time when budget constraints are increasing. Many forecasting techniques in use base the relationship between flying hours and demand as linear and do not consider the time factor in both demands and flying hours. Emphasis has been placed on finding forecasting techniques which accurately depict recoverable spares demand. How accurately can a time series forecasting model using flying hours and recoverable spares demand predict future recoverable spares requirements?

Justification

Many forecasting methods compute requirements based on the linear relationships between demand and flying hours without considering both the time factor and non-linearity involved in demands for aircraft recoverable spares and flying hours. In the thesis "An Alternative Forecasting Method for DRIVE," by Captain Alan Closson, he discussed an example of a model currently in use by the Air Force which assumes recoverable spares demand varies linearly with the number of flying hours (5:5). The model is the Distribution and Repair in Variable Environments (DRIVE) developed by the RAND Corporation. DRIVE's purpose is to ensure repair and distribution of recoverable components yields the best support available in regenerating spares to meet demands (6).

The DRIVE algorithm uses a four-quarter moving average to determine expected demands at bases. All the bases are then averaged to get a worldwide average. To get each bases demand rate, the worldwide demand rate per 1,000 flying hours is multiplied by the projected number of flying hours at the base. Each base's demand rate is based on the assumption demand varies linearly with the number of flying hours (6).

To test DRIVE's assumption, the Air Force Logistics Management Center (LMC) investigated the linear relationship of demand and flying hours since forecasts derived from worldwide demands are based on linearity. LMC researchers used

176 items consumed at four different bases with varied numbers of aircraft. The results of their study indicated demand does not vary linearly with the number of aircraft at a base (1).

Two other examples of requirements computation methods currently used by the Air Force which use linear causal relationships are the Peacetime Operating Stock Spares Estimates (POSSEM) and the Air Logistics Early Requirements Techniques (ALERT) which were studied in a thesis by Thomas Lockette (10). Lockette's research also indicated demand and flying hours are not just linearly related (10:8). The results of his thesis are described in more depth in Chapter II.

A technique to study spares forecasting which is not based on linearity is time series analysis. Time series analysis considers factors such as seasonality, trends, cycles, and time. Time series analysis techniques, such as Box-Jenkins, analyze data as it occurs over time to relate factors like seasonality, trend, and cycles. Seasonality is a condition observed when a systematic pattern occurs in time series data. An example is high demand in the winter and low demand in the summer for snow shoes (11:581). Trend is a condition observed when a time series shows consistent increase or decrease over time (11:585). A cycle is a recurring sequence of expansion and depression periods. Examples are business cycles which vary in length and

magnitude (11:567). By considering non-linearity over time between flying hours and demand, a time series forecasting model could improve future requirements computation and aid in deciding which recoverables to budget for and how many of each.

Scope and Limitations

Each aircraft weapon system is composed of hundreds of recoverable spares. Some of these spares can be used on multiple weapon systems while others are unique to their aircraft. Due to the magnitude of aircraft types and spares available, the scope of this thesis will be limited to analyzing C-135 aircraft monthly flying hours and recoverable spares demand for a random sample of spares from January 1978 through December 1985.

A large number of time series analysis and forecasting software are available with which to analyze data. The TIMES software program, which was developed under contract for the Air Force, and FORECAST MASTER software are used for data analysis and testing of both time series and simple exponential smoothing forecasting models. The TIMES program uses Fortran subroutines for time series analysis and forecasting. The program is available on the Cyber and Harris computers at the Air Force Institute of Technology (AFIT). It was recently adapted for use on personal computers at AFIT. TIMES does Box-Jenkins time series techniques for model building (20). FORECAST MASTER software by Scientific

Systems, Electric Power Institute, is capable of doing limited time series analysis, regression, and simple exponential smoothing as well as other forecasting techniques. The times series and exponential smoothing analyses are limited to the capabilities of each of these software packages.

Investigative Questions

Answering the following investigative questions will aid in the analysis and development of the time series and simple exponential smoothing models used to forecast C-135 spares requirements.

1. What type of statistical relationship exists between C-135 flying hours and demand in the transfer function models?

    a. What is the extent of correlation?
    b. Are there linear relationships between aircraft recoverable demands and flying hours?
    c. How are past C-135 spares requirements for a specific time period related to flying hours in one or more prior time periods?
    d. What seasonality or trend is in the data?

2. Which forecasting techniques best model the data?

    a. Do the transfer function models simulate the data pattern?
    b. What time series parameters were found in the Autoregressive Integrated Moving Average (ARIMA) model?

3. How accurately do the developed models predict demand?

    a. How do forecasts from the transfer function models compare with actual demand, univariate models', and simple exponential smoothing models' results?
    b. What modifications are needed?
    c. Will the models improve spares forecasting?

Methodology

Three types of models are built to compare the accuracy of forecast demand to actual demand for ten separate C-135 aircraft recoverable spares. Box-Jenkins time series techniques are used to develop two of these models on TIMES software. The first model is the multivariate or transfer function model where flying hours (independent variable) are used to predict spares demand. The second Box-Jenkins models developed for the ten spares are univariate models where past demand, indexed over time, is used to predict future demand. The third type of models used are simple exponential smoothing models developed using FORECAST MASTER software.

Once the models are developed, each forecasts one quarter of demand. These forecasts are then compared to the actual demand for the quarter. The models' forecasts are compared to the actual values by calcualting the mean absolute percentage error.

Summary

Due to recent budget cuts and an Air Staff directive, indepth research has been aimed at improving the forecasting of demand for aircraft recoverable spares. Results of research indicate that the relationship between flying hours and demand may not be linear. This thesis will investigate forecasting C-135 recoverable demand by using Box-Jenkins time series techniques on TIMES software. In Chapter II, a literature review is given on Box-Jenkins techniques followed

by a review of results found in three Air Force studies which implemented Box-Jenkins techniques in transfer function models. Since the results for the Box-Jenkins models will be compared to those found using exponential smoothing, a review will also be given on simple exponential smoothing and some of the studies researching it. To conclude Chapter II, a review is also given on the systems American Airlines uses to forecast recoverable aircraft spares. In Chapter III, the methodology for each step of the Box-Jenkins technique is reviewed as well as the data conversion steps used to prepare the spares data. Chapter IV is an analysis and description of the models and provides a comparison of their respective forecasts. Chapter V presents the conclusions of the research and suggests areas of further research.

II. Literature Review

Overview

This section opens with a brief discussion of the Box-Jenkins time series technique for developing a forecasting model. This is followed by a review of three studies done on Air Force assets which used Box-Jenkins time series techniques. The next section describes the simple exponential smoothing method which is also used to forecast spares demand so a comparison can be made between the results from Box-Jenkins techniques and simple exponential smoothing. The final section describes the forecasting methods used by American Airlines.

Box-Jenkins

Box-Jenkins is a time series forecasting method which uses a complex, computer-based procedure to produce autoregressive, integrated moving average (ARIMA) models. It can adjust for seasonal and trend factors and estimate appropriate weighting parameters (9:123). Box-Jenkins consists of a four-step process of identification, estimation, diagnostic checking and forecasting. For the first step of identification, George Box and Gwilym Jenkins recommend that fifty or more observations are needed before their correlogram methods provide a reliable guide to model selection for monthly seasonal data such as spare parts demand (2:64). In the identification

step, historical data are analyzed to identify a model. Unknown parameters are estimated for the models in the estimation step. During diagnostic checking, the models are tested for validity and, if valid, they are used in the fourth step of forecasting where future values are likely to be observed based on the accuracy of the developed model (2:64). Box-Jenkins steps are used to develop several models that explore the relationships within and between variables such as demand and flying hours. Once the initial relationships are found, they are combined into a final transfer function model for forecasting.

Box-Jenkins is a powerful time series analysis tool that considers relationships between variables and their relationships with time. Advantages of Box-Jenkins are that it allows a wide choice of weights for the user to identify much more subtle patterns in the data and it is very powerful for forecasting 1 to 2 years ahead when little is known about the underlying pattern of the data (20:292). Since Box-Jenkins is more than a technique, its' philosophy is based on the principle where the simpler the model, the better it is so long as it passes diagnostic checks (11:98). Disadvantages of Box-Jenkins are that it is complex and difficult to understand and it is expensive in its use of computing time (11:98). Box-Jenkins is a complex technique to understand. In the 1970's, it was usually run on a mainframe computer which was time consuming and expensive. Today,

software exists that runs complex methods such as Box-Jenkins on personal computers allowing a hands on approach to computer analysis with less expense.

Research Studies Using Box-Jenkins Techniques

Three studies using Box-Jenkins time series techniques were accomplished recently by Air Force personnel. The first was done in 1982 by Singpurwalla and Talbott (15:552). They used time series analysis to investigate the interrelationships between alert availability and flying hours for Air Force C-141 aircraft. Singpurwalla and Talbott used the Box-Jenkins method to develop a transfer function model. Using the final transfer function model, their results indicated flying hours do have an effect on the alert availability specified by the functional form of their developed final transfer function model (15:582). Singpurwalla and Talbott concluded their final equation supported the expression ". . . the more you fly, the less you fail" (15:582).

In 1983, Larry Taylor did a masters thesis on using time series analysis to develop forecasts for recoverable spares. He used five F-16 line replacement units (LRU) that impaired mission capability (MICAP) for the week of 12 June 1983 (16:8). He wanted to demonstrate that the number of demands per flying hour is not a linear ratio. Taylor chose time series analysis because it does not rely on cumulative averages, but uses actual data as it occurs through time to make forecasts (16:8). Taylor not only noted

that the "linearity" assumption caused support problems, he also noted that demands per flying hour data are collected over time so time is also a factor. Since time is a factor, there are underlying interrelationships between demand and flying hours (16:28). Time series analysis is a viable approach to help determine if those relationships are linear or not.

Taylor used the TIMES software package for analysis. In his findings, Taylor noted a seven period time lag for demand before flying hours had an effect on it. It was also shown both flying hours and demand were nonstationary and had auto-regressive and moving average components indicating possible non-linearity (16:69-70). Taylor recommended further study since he used less than 50 observations and recommended using at least 50 and preferably 100 observations to realize the full benefit of Box-Jenkins time series analysis (16:72).

In a third study using Box-Jenkins, Thomas Lockette did a masters thesis in 1984 to accomplish a time series analysis of C-130 recoverable spares requirements to identify the relationship between C-130 flying hours and spares requirements. The study was accomplished, not to develop a forecasting model, but to demonstrate a methodology to be used to identify relationships for various logistics times series for other weapon systems (10:ii).

Lockette examined the relationships between flying hours and expenditures. His research was done to investigate how

Box-Jenkins time series techniques could be used to develop models which would forecast Program Objective Memorandums (POMs). He then compared his formula to the Peacetime Operating Stock Spares Estimation System (POSSEM) linear regression technique (10:4). Lockette attempted to demonstrate that current linear regression techniques used to forecast obligations could be improved by using Box-Jenkins techniques to recognize time factors inherent in the data (10:75). He obtained conflicting results and mentions the need for further study using demand versus flying hours instead of obligations and flying hours. He recommended using well over 50 data points since he could not confirm if his results, indicating the presence of some non-linearity, might have resulted from using a small number of data points (10:76).

Over each of these studies, the authors mentioned their results using Box-Jenkins time series techniques were limited due to the data constraints. This research attempts to build on these three previous studies by developing both the multivariate and univariate Box-Jenkins models to forecast aircraft demand and then comparing them to a currently used method of forecasting, simple exponential smoothing. Since the Box-Jenkins models' forecasts are compared to simple exponential smoothing, the next section reviews simple exponential smoothing and research results found using it.

Exponential Smoothing

Exponential smoothing is a type of moving average where past data points are not given equal weight. Recent data is weighted more heavily than older data. The value of a smoothing constant determines the level of weight assigned to most recent data. The smoothing constant takes on a value between one and zero, where small values smooth recent trends and large values emphasize recent demand conditions (18:53).

The formula for single exponential smoothing is:

$$S_{t+1} = aX + (1-a)S_t \tag{1}$$

where:

X = most recent actual value

S_t = the latest forecast

S_{t+1} = forecast for the next period

a = the smoothing constant (20:79).

Simple exponential smoothing is an extremely popular technique among forecasting practioners since the logic of the whole exponential smoothing process is based on the following premise: "If the forecast for a particular period was too high, reduce it for the next period; if it was too low, raise it!" (11:107). Advantages of exponential smoothing are that it is easy to computerize for a large number of items at low cost, easy to monitor, and easy to understand (11:98). The major advantage of exponential

smoothing is that it does not require a long history of data to get started. It captures the effect of all past data on the most previous forecast (18:53). Disadvantages of exponential smoothing mentioned by Makridakis and Wheelwright are; it lags shifts in demands, it can only be applied to short-run forecasts, it may overreact to randomness, and technically, problems arise in choosing smoothing constant values (11:110). Several studies have been done using exponential smoothing to analyze aircraft spares demand data for the Air Force.

In a study of Air Force spare parts done in 1984, Craig Sherbrooke analyzed worldwide base level demands for 1,027 recoverable spares over 48 months. He found that demand in consecutive months was not independent since many spares had mean demands that were not constant. He reported a model would be needed that would not assume demand through time is independent. Sherbrooke concluded exponential smoothing was a better predictor of mean demand since mean demand rates change over time and exponential smoothing will be more responsive to change (13:24).

In 1987, Sherbrooke did another study on aircraft recoverable spares. He compared the Air Force Recoverable Consumption Item Requirements (D041) system moving average rates to those found using exponential smoothing and Bayes predictions. Demand data were used from 560 C-5 aircraft first indenture non-engine items over 16 quarters. This

data was accumulated from the D041 system. Demand data for the A-10 airframe and F-16 engine/airframe were also used in further testing. Two important results Sherbrooke found were: (1) demand in any period is more highly correlated with recent demand than with earlier demand, (2) exponential smoothing techniques are superior to today's D041 moving average rates for estimating demand rates (14:11). In both his studies, Sherbrooke recommends a smoothing constant value of 0.4 because it reduced mean squared error and mean absolute error for the quarterly data (13:23).

A final step in searching the literature was to look for information on how United States commercial airlines forecast their recoverable spares. What follows is a brief summary of how American Airlines forecasts rotable requirements. Rotable is the American Airlines term for recoverable assets (17:1).

American Airlines

Air Force C-135 aircraft fly missions ranging from cargo and passenger transport to aerial refueling. They are physically structured similar to commercial aircraft and also have similar maneuverability and flight capabilities.

Due to the similarities of Air Force C-135's to commercial aircraft, requests were made to American Airlines for information on how they forecast recoverable spares. Mark Tedone, American Airlines Decision Technologies (AADT), has written an article for Interfaces titled "Reparable

Part Management" which is scheduled to be published some time in 1989. His article describes the new Rotables Allocation Planning System (RAPS) recently developed by AADT ". . . to provide forecasts of rotable parts demand, recommend least-cost allocations, and calculate the availability level associated with the optimal allocation of each part" (17:ii). The predecessor to RAPS is the Rotable Forecasting and Availability Control System (ROFACS). It was developed in the late 1960's and implemented in the mid 1970's. It was originally developed for a rigid mainframe computer. ROFACS generated demand forecasts using only time series methodology. For its time, ROFACS remained a valuable indicator of appropriate allocation levels. Since ROFACS used only time series methodology on a rigid mainframe computer, it was sometimes slow in responding to changes in aircraft utilization or major fleet expansions. Decision Technologies examined ROFACS in detail to uncover its deficiencies and started development of RAPS (17:3-4). RAPS uses linear regression to establish a relationship between parts removal and various functions of monthly flying hours to determine the absolute volume of demand (17:6-7). American Airlines also determines the patterns of demand through time using RAPS, which has a major influence on the total cost of an allocation (17:8). Overall, American Airlines has made multi-million dollar improvements in their inventory position by taking their older time series

methodology for a mainframe, finding its deficiencies, and using them to develop a new RAPS system which has exceeded expectations (17:15-16).

American Airlines flies a city hub system for aircraft and has set repair sites and flight routes. Their aircraft spend few hours sitting idle since a grounded aircraft lowers customer service. American Airlines used the ROFACS time series approach to forecast spares when mainframe computers were all that was available. They have recently changed to RAPS and now use linear regression techniques on real-time personal computer systems throughout their locations to forecast spares. RAPS is also used for recommending least-cost allocations of spares and calculating availability levels for optimum spares allocation. The RAPS implementation provided a multi-million dollar benefit to American Airlines and although they currently use linear regression without time series methods, it was a time series methodology which broke ground for the RAPS.

Summary

Chapter II provided an introduction to Box-Jenkins techniques and the four-step process of identification, estimation, diagnostic checking, and forecasting. A review was given of previous Box-Jenkins studies done on Air Force assets. After Box-Jenkins, simple exponential smoothing was reviewed as well as studies done by Craig Sherbrooke who

used simple exponential smoothing on Air Force assets. The chapter concluded with a discussion of how American Airlines forecasts recoverable spares.

In the Chapter III methodology, each of the Box-Jenkins analysis steps used to answer the investigative questions and lead to the development of a model will be discussed as well as the steps taken to obtain and prepare the flying hour and demand data for use with both Box-Jenkins and simple exponential smoothing models.

III. Methodology

Overview

This chapter opens with a description of the spares and flying hours data collection and preparation for Box-Jenkins. The next section describes the Box-Jenkins steps taken in using historical data to develop a model for forecasting. The steps of model identification, parameter estimation, and forecasting are the principal stages in the TIMES computer program that will be used. To avoid duplication of explanation, a general description will be given of each step since the detailed model formulation, plots, and tables will be shown in detail in Chapter IV. The final section briefly describes the software used to model the spares data using exponential smoothing.

Data Availability and Preparation

Flying Hours. Monthly C-135 flying hour data were obtained from the Air Force Inspection and Safety Center at Norton AFB, CA, for the period of January 1978 - March 1986. Ninety-six months were used for model building. Three months of data were withheld as a basis to compare the forecasts with the actual observations. The data are attached in Appendix A.

Recoverable Spares. The recoverable spares demand data for C-135 aircraft was obtained from the Analysis and Information Management Division (MMMA) at Headquarters, Air Force Logistics Command. The quarterly data were downloaded from a tape containing D041 data from January 1978 - March 1986. Ten C-135 spares were randomly chosen from a listing of 200 recoverable spares' data downloaded by HQ AFLC/MMMA. Table 1 lists the stock numbers and their description as they appeared on the D041. Throughout the thesis, the stock numbers are identified by the abbreviations in the third column of Table 1. The quarterly demand data are attached in Appendix A. Of the thirty-three quarters of data for each spare, seven quarters were missing. As with the flying hours, the quarter ending March 1986 was withheld as a basis for forecast comparisons. Asterisks appear in Appendix A next to the dates of the missing quarters of demand data.

Table 1.

C-135 Spares' Stock Numbers

Stock Number	Description	Abbreviations
1560 00 075 1401	FLFAIRING	FAIR01
1560 00 056 6631	FLPANEL ASSY	ASSY31
1560 00 011 0674	FLTAB ASSY	TAB74
1560 00 015 2153	FLFRAME	FRAME53
1560 00 055 5584	FLTAILPIPE	TAIL84
1560 00 055 5583	FLCOWL	COWL83
1560 00 055 5585	FLSLEEVE	SLVE85
1560 00 056 6632	FLPANEL ASSY	ASSY32
1560 00 056 6633	FLPANEL ASSY	ASSY33
1560 00 068 2535	FLFORK ASSY	FORK35

To find values for the missing quarterly data, an imputation-based procedure was used known as mean imputation where means from sets of values are used to fill in missing data (12:6). To obtain the sets of values for each spares' seven missing quarters, a modified Delphi technique was used. Three supply experts separately estimated the demand for each missing quarter by stock number by analyzing the pattern of available quarterly data. The mean of the experts' determinations was used as the demand for each of the missing quarters of data.

For data analysis, 32 of the 33 quarters were used for model building. The remaining quarter (Jan - Mar 1986), was withheld for comparison with forecasts from the models. To match the 96 months of flying hours data, the 32 quarters of data were converted to 96 months by dividing each quarter's spares demand by 3. In a Sherbrooke study, he briefly mentioned converting quarterly data to monthly is feasible since it induces an insignificant amount of error. Overall, the amount of error induced depends totally on the distribution of the data and the magnitude of the values (13:10).

Box-Jenkins Model Development

Box-Jenkins time series analysis uses a four-step process of model identification, parameter estimation, diagnostic checking, and forecasting. These four steps are divided into three stages. Initially, a general class of forecasting

models is postulated. In stage 1, a specific model is tentatively picked as the best forecasting method for that set of data. In stage 2, the model is fitted to the historical data and tested. If it is not adequate, stage 1 is repeated. Once the model passes the checks, it is used to develop a forecast in stage 3 (19:173).

Model Identification

In the model identification stage, the historical data for flying hours and demand are separately analyzed to identify the relationships that exist within each time series. Identifying possible models involves the concepts of stationarity, correlation, autocorrelation, and partial autocorrelation. First, to develop each individual univariate time series model, each set of data must be stationary. A data set is considered to be stationary if its values (observations) fluctuate around a constant mean with a constant variance. Stationarity is checked by observing plots of the original data and residual plots output by the TIMES computer program. If a model is non-stationary, two commonly practiced techniques for making it stationary are to transform the original data into the natural logarithm of the original or to difference the data. First differencing of data is employed when just the mean is changing. Second differencing is usually done when both the mean and slope are changing. First differencing is accomplished by subtracting successive values from one another and using

these values as the new data set. The first differenced series has one less point than the original data. Second differencing is accomplished using the first differenced data set, differencing it again, and then using that series. A second differenced data set has two less data points than the original data (4). Once the data are stationary, development of the models takes place.

In developing each model, correlation, autocorrelation, and partial correlation need to be known. Correlation is the association or mutual correspondence between two variables and describes what happens to one of the variables if there is a change in the other (19:174). Autocorrelation describes the association or mutual dependence of the same variable at different time periods. Autocorrelation is critical since ". . . autocorrelation among successive values of the data is a key tool in identifying the basic pattern (or rather the model corresponding to it) that describes the data" (19:174). Partial autocorrelations are analogous to autocorrelations because they indicate relationships of the time series values to various time lagged values of the same series. They differ from autocorrelation since they are computed for each time lag after the effect of all other time lags on the given one, and on the original data are removed (16:30).

The autocorrelation is used to help identify the time series data pattern, test for stationarity, and identify a model for the time series. The autocorrelation coefficient

value which measures the linear relationship between two time series observations is always between -1 and +1. If the value is near 0 (zero), the two observations are linearly independent. If the value is near -1 or +1, the two observations are more linearly dependent (10:17). Once each model is stationary and all the autocorrelation coefficients are known, the autocorrelation coefficients are converted to an autocorrelation function (ACF). Partial autocorrelation functions (PACF) are also determined. By looking at the patterns of the ACF and PACF, a tentative model is developed which could indicate the presence of autoregressive (AR) or moving average (MA) parameters for an Autoregressive Integrated Moving Average (ARIMA) model (19:178).

Once the models for both flying hours and demand are determined to be either AR or MA, or a combination of both, they can be written, for example, as either an ARIMA (p,d,q) or an ARMA (p,q) in Box-Jenkins notation. The number of significant spikes in the autocorerelation and partial autocorrelation functions are denoted by the letters p and q. The d represents the level of differencing where zero means no differencing was used. Now that the models are identified, the next step is parameter estimation.

Parameter Estimation

After identifying the tentative model, the parameter values for AR or MA or both are estimated from the data. The TIMES program is run on an AFIT personal computer to

obtain the parameter estimates which minimize the mean squared errors (21:12). Once the parameters are estimated for the tentative model, diagnostic checks are performed to test the model adequacy.

Diagnostic Checking

"A model is considered adequate if the residual differences between the individual time series observations and the forecast using the tentative model are white noise" (10:21). White noise means the residuals show no linear relationships between themselves so they cannot be forecast by an improved model. Box and Jenkins emphasize several checks that should be done to test model adequacy. The first check strongly emphasized by Box and Jenkins is to visually inspect the plot of the residuals themselves (3:289). In these plots, the mean should be near zero and should not be changing over time. The residual variance should not change over time either.

The second check recommended is an autocorrelation check on the residual ACF and PACF to make sure there are no significant spikes which could indicate more AR or MA parameters are needed (3:290). A third check for model adequacy is the Portmanteau lack of fit test. This test involves solving for a variable Q and comparing it to Chi-Square values at selected confidence intervals with the same degrees of freedom. If the Portmanteau Q-value is less than the Chi-Square value at

the same degrees of freedom, the model surpasses the tested confidence level (3:292). The fourth test to check is model inadequacy arising from changes in parameter values. The parameter values should remain constant over time (3:293).

Four other diagnostic checks used to check a model were discussed in LOGM 630, Forecasting Management, by Lieutenant Colonel Bruce P. Christensen (4). The four other checks are:

1. Cumulative Periodogram. This periodogram is a Fourier transform of error covariance and is an output from the TIMES computer program. Ideally, the periodogram will show a diagonal line through a rectangle which indicates pure white noise and ensures additional seasonality is not in the residuals (4).

2. Histogram of the Residuals. The residual histogram indicates if residuals are distributed normal or not. If they are not normal, the model can still be good but care must be taken in giving confidence levels. The histogram is also an output of TIMES (4).

3. Variance of Residuals. The smaller the value of the variance of residuals, the better the model. The variance of residuals is used to compare alternative models. The better model is usually the one with the lowest residual mean square. This value is calculated and also output by TIMES (4).

4. Power Spectrum. The power spectrum shows whether or not additional seasonality exists in the residuals. The power spectrum is a Fourier transformation of autocovariance. Ideally, it is a smooth horizontal line across a rectangle (4).

Once each model for flying hours and demand pass the diagnostic checks, they are considered prewhitened and are ready to be combined into a two variable (multivariate) model called the transfer function model. The transfer

function model must pass through the same steps of identification, parameter estimation, and diagnostic checking as the univariate models already discussed.

Transfer Function Model

As univariate models, the time series of flying hours and demand were separately analyzed to identify the "within" relationships in each time series. In the transfer function model phase, both the flying hours and demand models are prewhitened and the residuals from the two series are analyzed to identify the "between" relationships of the two models. The two variable model is a transfer function model.

The transfer function model now consists of residuals from the prewhitened flying hours and demand models. The residuals are analyzed to identify the relationships which exist between the two time series. Flying hours is the independent univariate and demand is the dependent univariate. Noise parameters may also be added to the transfer function model to identify noise which is not white noise (totally random) left by the two univariate models. Together they form the final transfer model used to forecast demand.

The general form of the transfer function model is:

$$Y_t = s^{-1}(B)w(B)X_{t-1} + N_t \qquad (2)$$

$$N_t = \emptyset^{-1}(B)\theta(B)a_t \qquad (3)$$

where:

a_t = white noise

s,Ø,and w = parameter values

X_t = prewhitened independent/input series (flying hours)

N_t = noise

Y_t = prewhitened dependent/output series (spares demand) (3:362).

Exponential Smoothing

The ten separate spares models were built using the simple exponential smoothing program on FORECAST MASTER personal computer software by Scientific Systems, Electric Power Research Institute, 1986. Each model was built with an a = 0.4 as recommended by Sherbrooke. Each model was then used to forecast its respective demand for the period January - March 1986.

Comparison of Model Forecasts

Once the Box-Jenkins transfer function, Box-Jenkins univariate, and simple exponential smoothing models are developed and tested, each model is used to forecast demand for the Jan - Mar 1986 quarter for each of the spares. To compare the forecasting accuracy of the three techniques,

the mean absolute percentage error is calculated for each forecast. The mean absolute percentage error is calculated by subtracting the forecast demand value from the actual demand value and then the absolute value is taken. The absolute value is then divided by the actual value and multiplied by 100 to make it a percentage. The mean absolute percentage error was chosen since it is used to evaluate and compare a single observation forecast by the three different models (4). In the tables shown in Chapter IV, the mean absolute percentage error is denoted as the MAPE.

Investigative Questions Research

As the models are built and used to forecast, the results are used to answer the investigative questions asked in Chapter I. Building and analyzing the transfer function models leads to an answer for investigative question 1 which is:

1. What type of statistical relationship exists between C-135 flying hours and demand in the transfer function models?

Investigative questions 2 and 3 are answered once the models are built and the results of the models' forecasts are compared. Questions 2 and 3 are:

2. Which forecasting techniques best model the data?

3. How accurately do the developed models predict demand?

Summary

The Box-Jenkins four-step process of model identification, parameter estimation, diagnostic checking, and forecasting was used to develop multivariate models that related the relationships within and between flying hours and demand to forecast future spares demand. The four-step process was also used to build univariate demand models which forecast demand based on the pattern and relationships in the past demand. The simple exponential smoothing models based future spares demand on recent past demand in determining the forecast. Both the univariate models and simple exponential smoothing models were developed to compare forecasting accuracy with the transfer function models. In Chapter IV, a step-by-step description of the Box-Jenkin four-step process is given with TIMES output shown to aid in analyzing the models. The results of both the Box-Jenkins and simple exponential smoothing forecasts are compared to the actual spares demand.

IV. ANALYSIS AND RESULTS

Introduction

This chapter describes and analyzes the steps used in developing each model and provides a comparison of the models forecasting results for each of the Box-Jenkins multivariate (transfer function models), Box-Jenkins univariate, and simple exponential smoothing spares forecasting models for data spanning 1978 - 1985. The chapter opens with a discussion of each Box-Jenkins step used to form the univariate flying hours and spares time series models which were then used to form the transfer function models for forecasting. The section concludes with an analysis of the multivariate forecasting results.

Second, a detailed example is given of the steps taken in buiding one of the univariate Box-Jenkins models where past demand data are used to predict future demands. In the multivariate models, the relationships between and within flying hours and demands were used to build a model to forecast. A discussion of the univariace models' forecasting results is given at the end of this section.

Third, the results of forecasting demand using simple exponential smoothing is shown for the ten spares. The chapter concludes with a comparison of the forecasting results, a discussion of the answers found for the investigative questions asked in Chapter I, and a summary.

Transfer Function Model Development

To form the multivariate time series models for each of the ten spares, the flying hours data and spares data were used to form prewhitened univariate models. They were then combined to form the ten transfer function models used to forecast spares demand. A description of the steps used in developing the univariate model for the independent variable (flying hours) is described below.

Flying Hours Identification. Before the transfer function model can be formed, each individual series must be prewhitened. The identification step is the first step toward prewhitening the flying hours data. The flying hours data for 96 months (Appendix A) were analyzed using TIMES and FORECAST MASTER software. Prior to analysis, the logarithmic function of the flying hours data was taken because the flying hours consisted of very large monthly numbers compared to monthly demand for the ten spares. Taking the logarithmic function of the flying hours reduces the magnitude of the residuals so impulse response weights can be determined during development of the transfer function model.

To start, FORECAST MASTER was used to obtain a plot of the transformed data (Figure 1) and TIMES was used to perform an initial identification of data stationarity. The ACF did not drop rapidly to zero and the TIMES run showed that the first difference of the data had the least

amount of white noise. To make the data more stationary, the first difference was accomplished on the data and plotted on FORECAST MASTER (Figure 2). The plot now appears stationary with a constant mean and variance.

Now that the data are stationary, identification of potential models takes place. Plots and tables of the ACF and PACF for lags 1 - 36 of the first differenced data are shown in Figures 3 and 4 respectively. The ACF and PACF plot shows significant spikes at lags 1, 3, 4, 8, and 12. Significant spikes extend beyond 1/2 the standard error for lags 1 - 3; one standard error for lags 4 - 6; two standard errors for lags 7 - 12; and three standard errors for lags greater than 12 (4). The significant spikes at 4, 8, and 12 indicate a possible seasonality every four time periods. The significant spikes at 12, 24, and 36 also indicate a possible 12 period seasonality. Lags 1 and 3 indicate possible weak moving average and autoregressive patterns. Based on the examination of the ACF and PACF, possible starting models for the iterative process of identifying the most parsimonious (simple) model were the ARIMA's

$$\text{Ln } (1,1,1)*(0,0,1)_4,$$

$$\text{Ln } (1,1,0)*(0,0,1)_4*(0,0,1)_{12}, \text{ and}$$

$$\text{Ln } (0,1,1)*(0,0,1)_4*(1,0,0)_{12}.$$

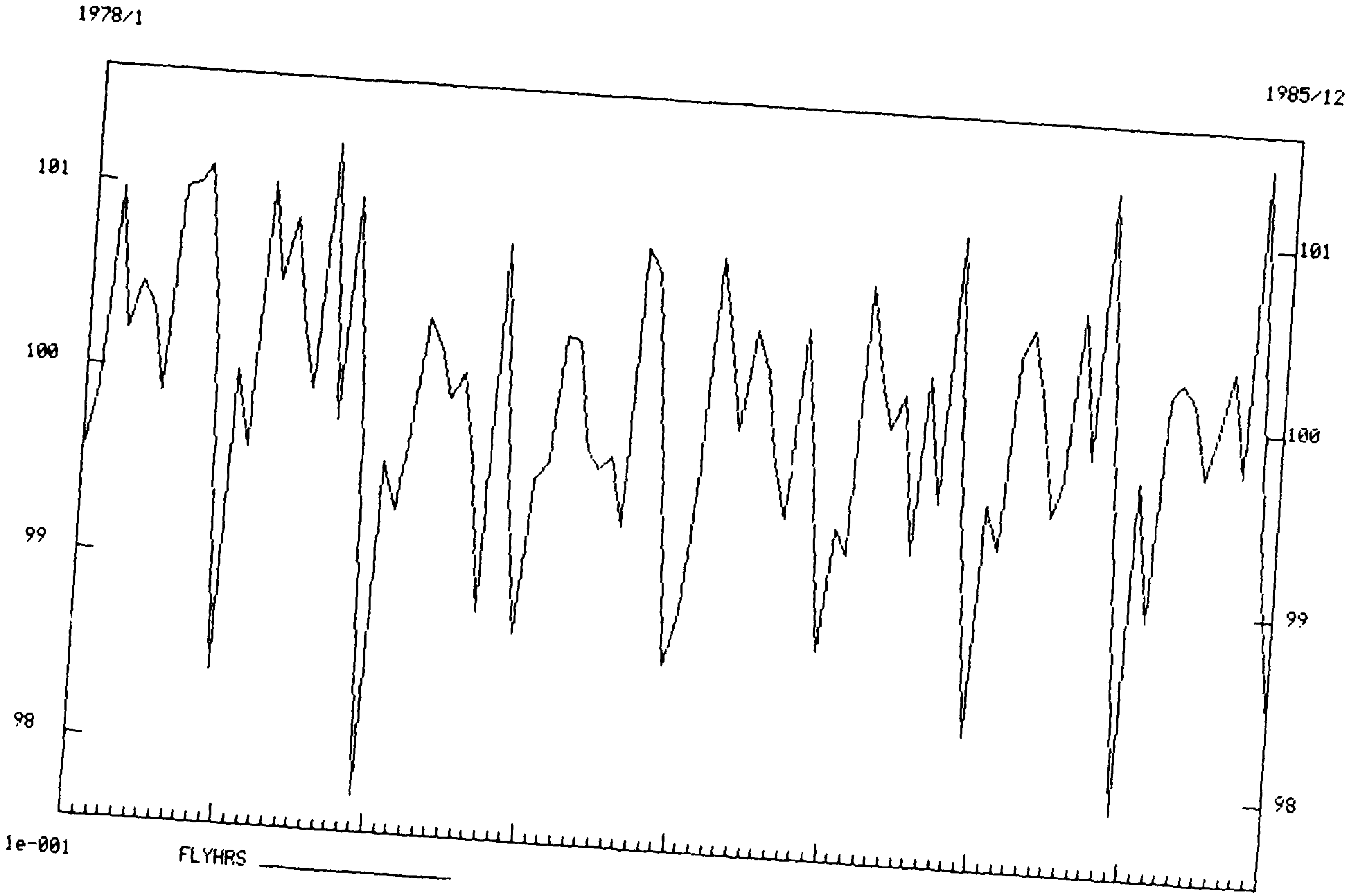

Figure 1. Plot of Transformed Flying Hours Data

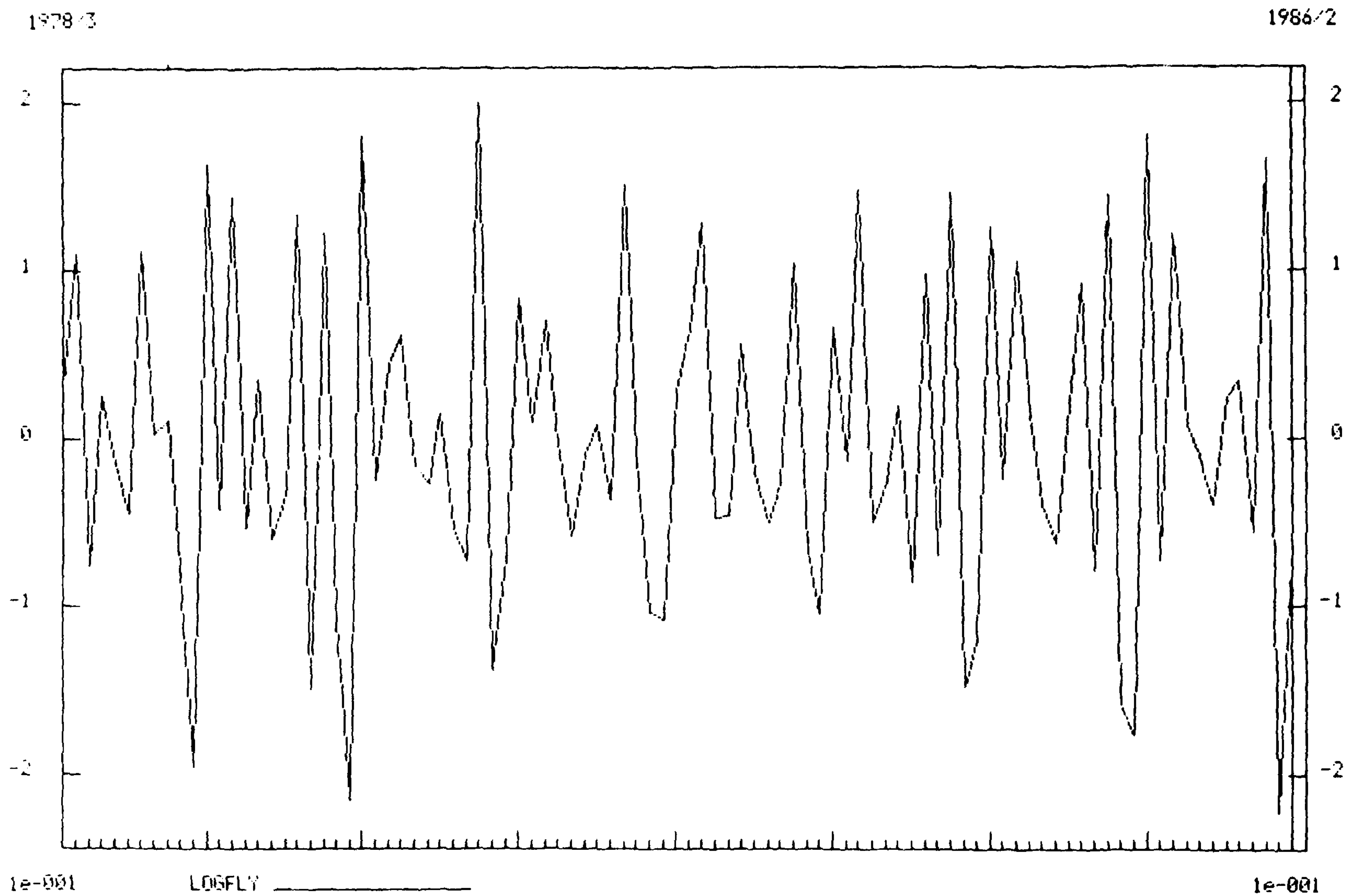

Figure 2. Plot of First Difference of Transformed Data

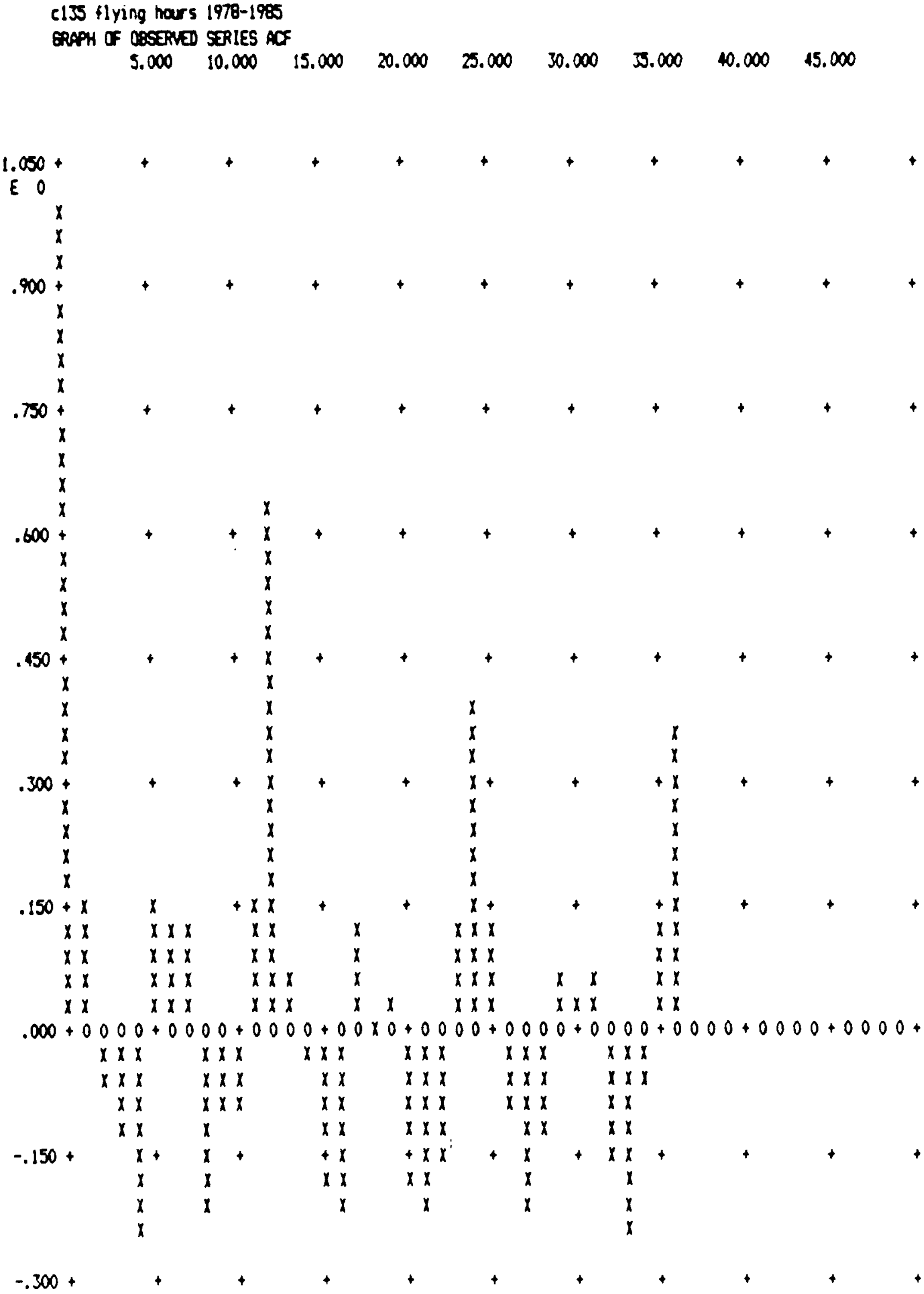

Figure 3. Flying Hours ACF Plot

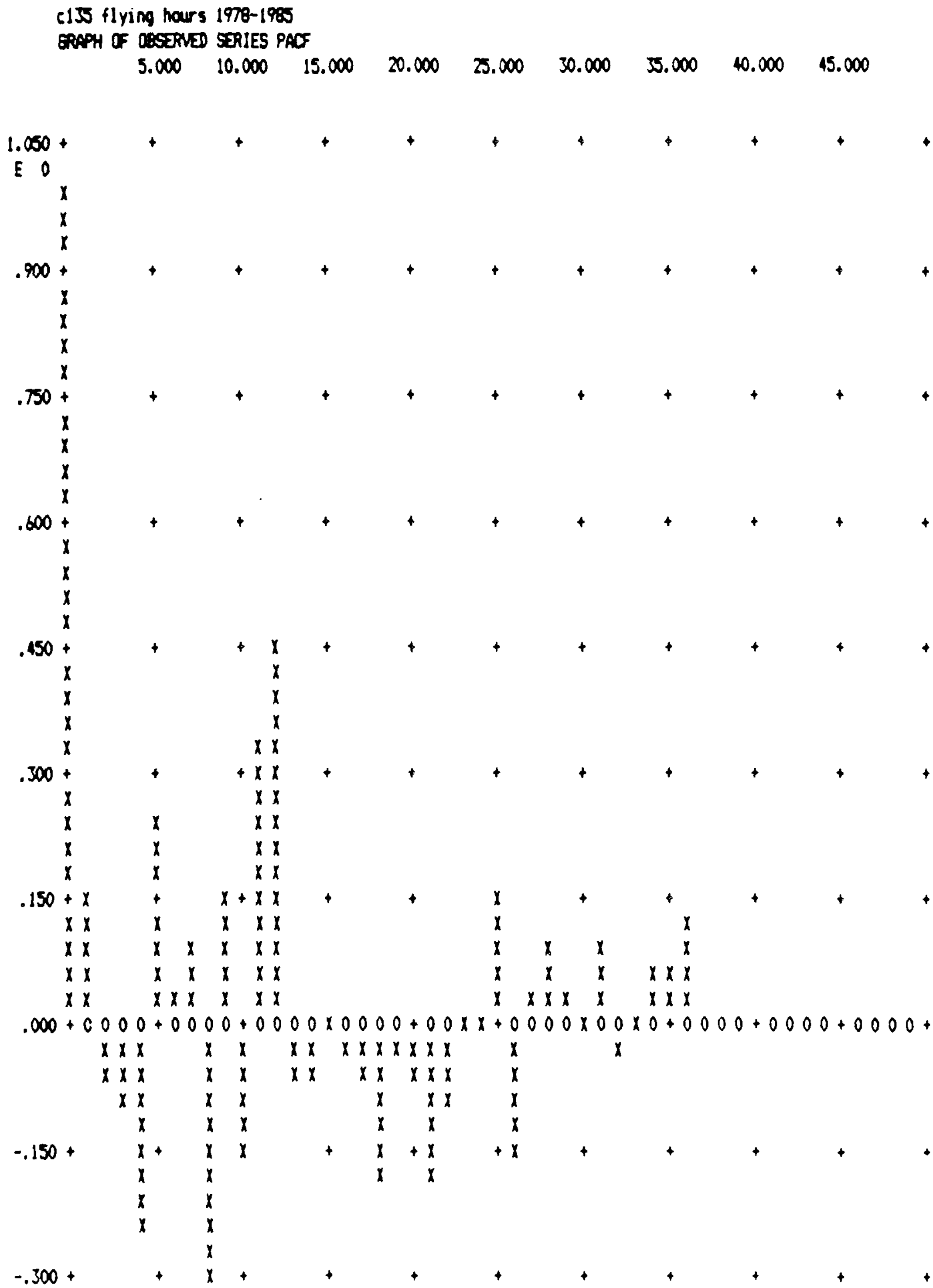

Figure 4. Flying Hours PACF Plot

The ARIMA Ln $(0,1,1)*(0,0,1)_4*(1,0,0)_{12}$ has no AR function with a difference of order 1, and an MA of order 1 in the first set of parentheses. The second set of parentheses indicates an MA seasonal term of order 4. The third set of parentheses indicates a seasonal AR term of order 12. Once possible models are selected, the next step is to run the estimations to see which model has the lowest residual mean square and Chi-square value.

Flying Hours Estimation. Parameter values for the ARIMA models:

$$\text{Ln } (1,1,1)*(0,0,1)_4,$$

$$\text{Ln } (1,1,0)*(0,0,1)_4*(0,0,1)_{12}, \text{ and}$$

$$\text{Ln } (0,1,1)*(0,0,1)_4*(1,0,0)_{12}$$

were estimated using the TIMES software. The ARIMA Ln $(0,1,1)*(0,1,1)_4*(1,0,0)_{12}$ had the lowest residual mean square (25.3 versus 32 and 36.7) and the lowest chi-square value (25.7 with 36 degrees of freedom) of the three models. The parameter values estimated by TIMES for the AR and MA parameters are shown in Figure 5. Once the model is selected, the next step is diagnostic checking where several tests are performed on the chosen model to test its validity.

SUMMARY OF MODEL 1

DATA - Z = c135 flying hours 1978-1985 96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(Z(T)+ .00000E+00)

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	12	.70996E+00	.56041E+00	.85951E+00
2	MOVING AVERAGE 1	1	.78543E+00	.64276E+00	.92809E+00
3	MOVING AVERAGE 2	4	.34907E+00	.12349E+00	.57465E+00

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.20208E+00	80 D.F.	RESIDUAL MEAN SQUARE	.25261E-02
NUMBER OF RESIDUALS	83		RESIDUAL STANDARD ERROR	.50260E-01

Figure 5. Flying Hours Parameter Values/Model Summary

Flying Hours Diagnostics. The chosen model for diagnostic checking is the ARIMA Ln $(0,1,1)*(0,0,1)_4*$ $(1,0,0)_{12}$.

The model equation is:

$$(1-\Phi B^{12})(1-B)(LnX_t) = (1-\Theta B)(1-\phi B^4)e_t \qquad (4)$$

where:

- B = the backshift operator and is equivalent to X_{t-n} and n is the superscript above each B in the Box-Jenkins notation.
- Φ = the seasonal autoregressive parameter value
- Θ = the moving average parameter value
- ϕ = the seasonal moving average parameter value.

Performing the diagnostic checks validates the model to ensure it follows the pattern of the data. Some of the checks performed were to examine the residual ACF and PACF, to compare the chi-square value at a 95% confidence interval, and to analyze the cumulative periodogram, histogram, and power spectrum of the residuals.

Tables 2 and 3 show the standard error values for the residual PACF and ACF. No significant spikes remain, indicaing the model cannot be significantly improved by adding more parameters. The Chi-square test determines whether the group of values of the autocorrelations is significantly different from zero. If the Chi-square value from a table of computed Chi-square values at various confidence levels is larger than

the Chi-square value estimated for the model, then the data are random with no pattern (3:291). This test is the Portmanteau Lack of Fit Test. For the flying hours ARIMA model chosen, the Chi-square value is 25.7 for 36 degrees of freedom. The table value for a 95% confidence interval and 36 degrees of freedom is greater than 43 (3:522).

Figure 6 shows the Cumulative Periodogram. Pure white noise would result in a perfect diagonal line through the periodogram. This figure shows a good periodogram indicating just white noise is present. Figure 7 shows the histogram of residuals. It has a normal shape and also confirms the residuals are white noise as desired. Figure 8 is the Power Spectrum which also supports the other tests in indicating the residuals are white noise. A good power spectrum is determined by placing a ruler horizontally across the spectrum. If the ruler picks up the connecting points with no breaks, the spectrum is acceptable as this one is.

To summarize, the ARIMA Ln $(0,1,1)*(0,0,1)_{4}*(1,0,0)_{12}$ is the univariate model selected to be the independent/input variable used for identifying the final transfer function models. The next step is to prewhiten the dependent/output variable which is spares demand.

Spares Demand Prewhitened. Since the flying hours portion of the transfer function (with possible noise parameters) model is used to predict the spares demand as the independent variable, it is not necessary to determine

the actual parameter values for the demand data. Prewhitening of each of the ten spares consisted of calculating the first difference of each data set since it had the most stationary data. The demand data is combined with the flying hours model and formulation of the multivariate transfer models begin for each of the spares.

Table 2. Flying Hours PACF of Residuals

PARTIAL AUTOCORRELATIONS

DATA - THE ESTIMATED RESIDUALS — MODEL 1

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES =-.33023E-02
ST. DEV. OF SERIES = .49532E-01
NUMBER OF OBSERVATIONS = 83

1- 12	-.02	-.07	-.03	.00	.10	.07	.00	.03	.19	-.03	.11	-.15
13- 24	-.20	.02	-.04	-.08	.04	-.10	.02	-.12	.00	-.17	.04	-.02
25- 36	.17	-.10	.03	-.03	.11	-.02	.05	-.10	-.16	-.09	.13	.06
37- 39	.00	.09	.01									

Table 3. Flying Hours ACF of Residuals

AUTOCORRELATION FUNCTION

DATA - THE ESTIMATED RESIDUALS -- MODEL 1

DIFFERENCING - ORIGINAL SERIES IS YOUR DATA.

DIFFERENCES BELOW ARE OF ORDER 1

ORIGINAL SERIES
MEAN OF THE SERIES =-.33023E-02
ST. DEV. OF SERIES = .49532E-01
NUMBER OF OBSERVATIONS = 83

1- 12	-.02	-.07	-.02	.01	.10	.07	-.02	.02	.18	-.03	.09	-.15
ST.E.	.11	.11	.11	.11	.11	.11	.11	.11	.11	.12	.12	.12
13- 24	-.19	.08	.01	-.06	.03	-.11	-.01	-.07	-.08	-.19	.05	-.03
ST.E.	.12	.12	.12	.12	.12	.12	.12	.12	.13	.13	.13	.13
25- 36	.16	-.08	-.12	.01	.04	.02	-.03	-.03	-.15	.10	.11	.08
ST.E.	.13	.13	.13	.13	.13	.13	.13	.13	.13	.14	.14	.14
37- 39	-.09	.06	.04									
ST.E.	.14	.14	.14									

MEAN DIVIDED BY ST. ERROR = .60740E+00

TO TEST WHETHER THIS SERIES IS WHITE NOISE, THE VALUE .25731E+02
SHOULD BE COMPARED WITH A CHI-SQUARE VARIABLE WITH 36 DEGREES OF FREEDOM

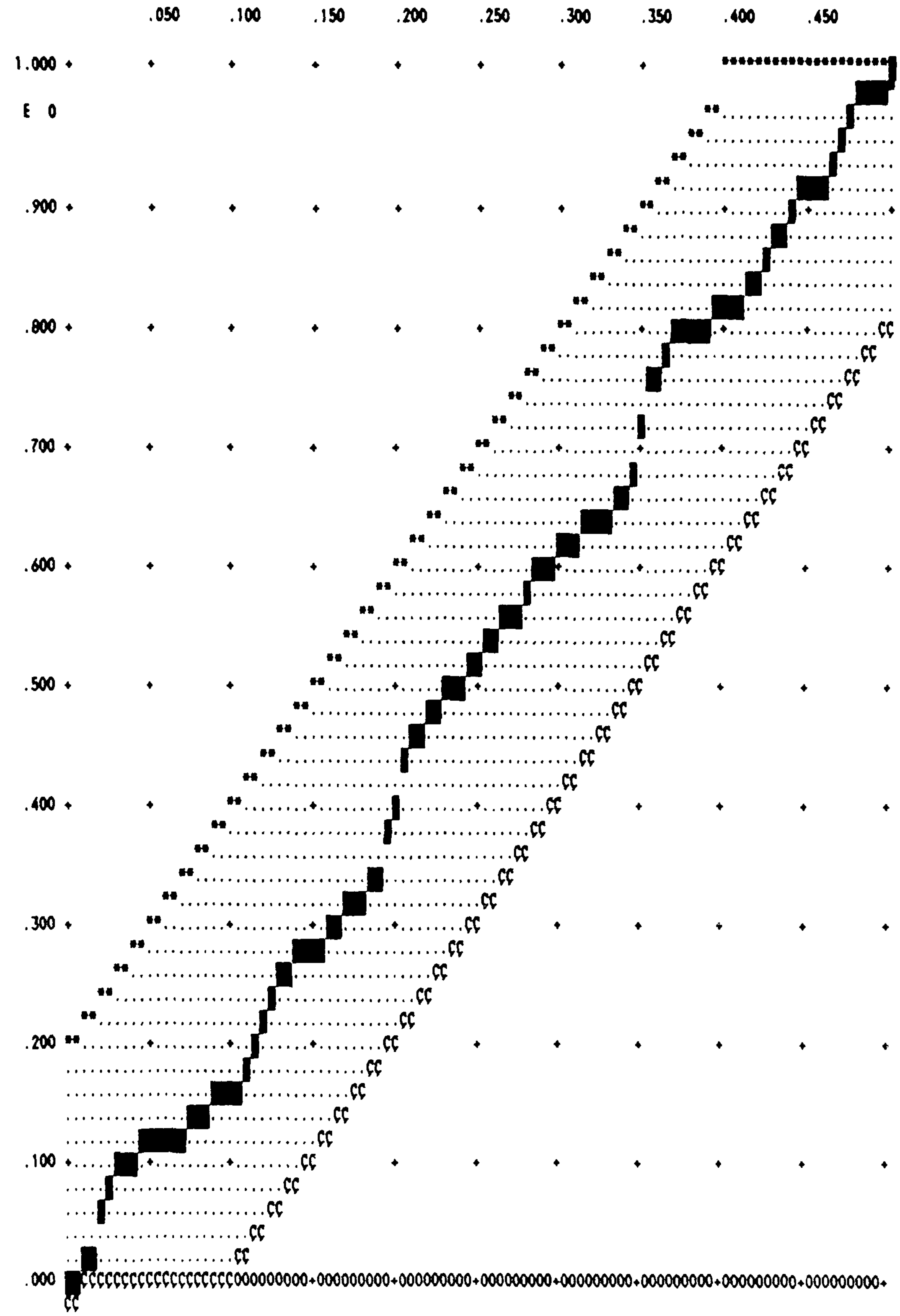

Figure 6. Flying Hours Cumulative Periodogram

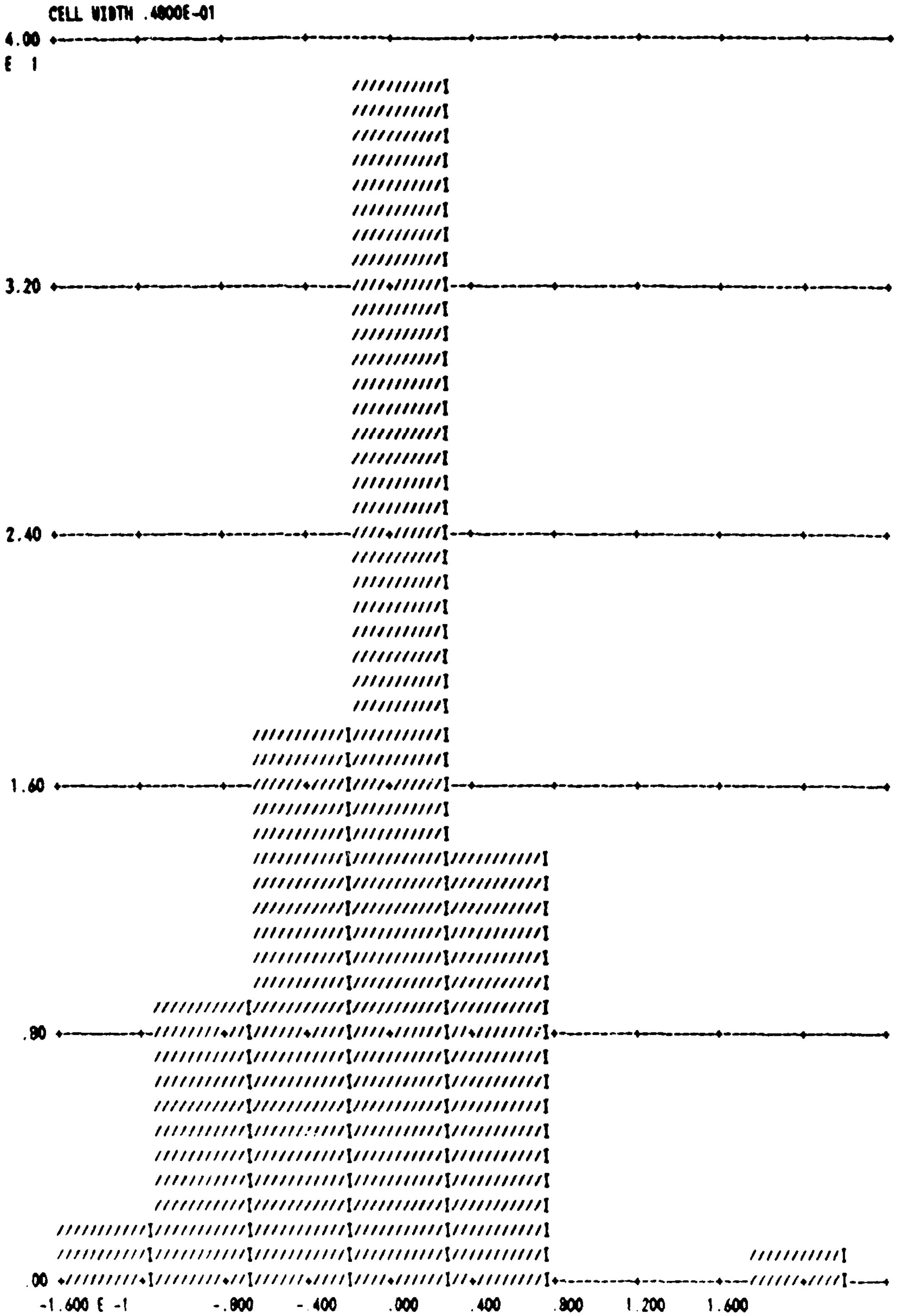

Figure 7. Flying Hours Histogram of Residuals

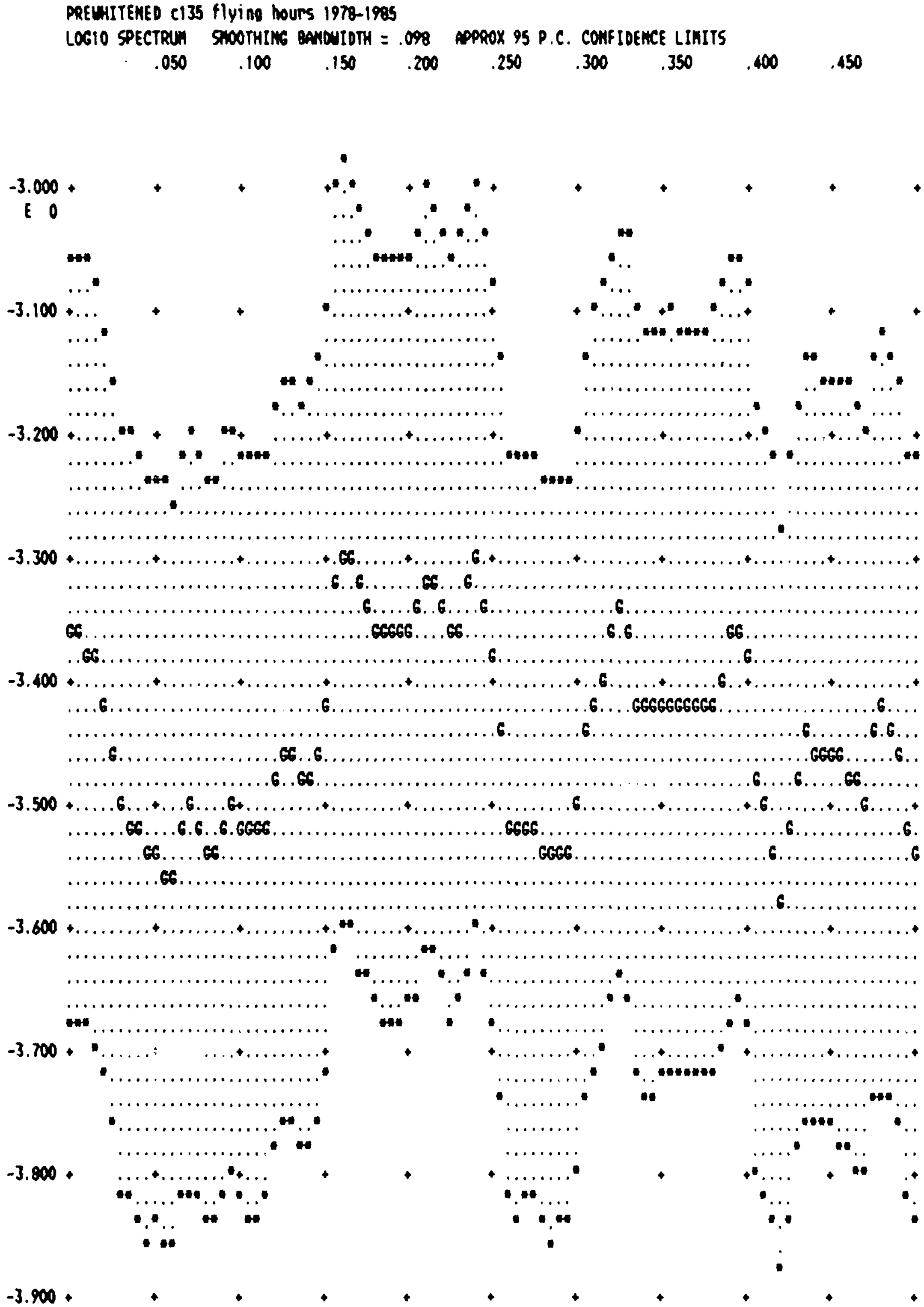

Figure 8. Flying Hours Power Spectrum

Transfer Function Model Formulation. For an example of the steps taken to form a transfer function model once the univariate models are prewhitened, the TAB74 spare's data are used. The computer output and model parameter results for the other nine spares are located in Appendix B.

To preview, a second form of the general equation for a transfer function model shown in Eq (2) is:

$$(1-s_1 B - . . . -s_r B^r)Y_t = (w_0 -w_1 B- . . . -w_s B^s)X_{t-b} + N_t \quad (5)$$

where:

- r = the number of cogent past Y_t and is derived from the pattern of the cross correlation. The value of r should equal the number of "start-up" values before the b lag.

- b = the number of cross correlations equal to zero before a significant cross correlation is observed. In other words, b is the number of periods until the effect of a change in X_t (flying hours) affects Y_t (demand).

- s = the past X_t values. Y_t and X_t are the same as those defined in Eq (2).

The model is denoted as an (r,s,b) model (3:377-379).

To identify a transfer function model, the steps consist of:

(1) deriving rough estimates of the impulse response weights (v_j) - output in TIMES.

(2) use values from (1) to estimate r, s, and b.

(3) use values from (1) and (2) to obtain initial estimates of s and w (3:378).

The values of r, s, and b are estimated by using the cross correlations and impulse response weights from TIMES.

TAB74 Transfer Function Development. In developing the TAB74 transfer function model to forecast, the flying hours model is combined with the TAB74 monthly data in a TIMES Fortran program. The same steps of identification, estimation and diagnostic checking are performed.

First, an identification run is done on TIMES to obtain the impulse response weights and cross correlation values. Table 4 shows the values TIMES calculated for the impulse response weights for TAB74. Lag 1 has a large negative number and this value appears in the plot of the cross correlations shown in Figure 9. Table 5 shows the cross correlation values which are also plotted in Figure 9. The series 1 data in the left column of Table 5 appear on the right hand side of the cross correlation plot in Figure 9. It is the right hand side of zero which is used to help determine r, s, and b along with the plot of the estimated impulse response weights in Figure 10.

Table 4.

Estimated Impulse Response Weights

K	V(K)
0	-.847
1	-2.64
2	.121
3	-1.73
4	.690
5	.649
6	.867

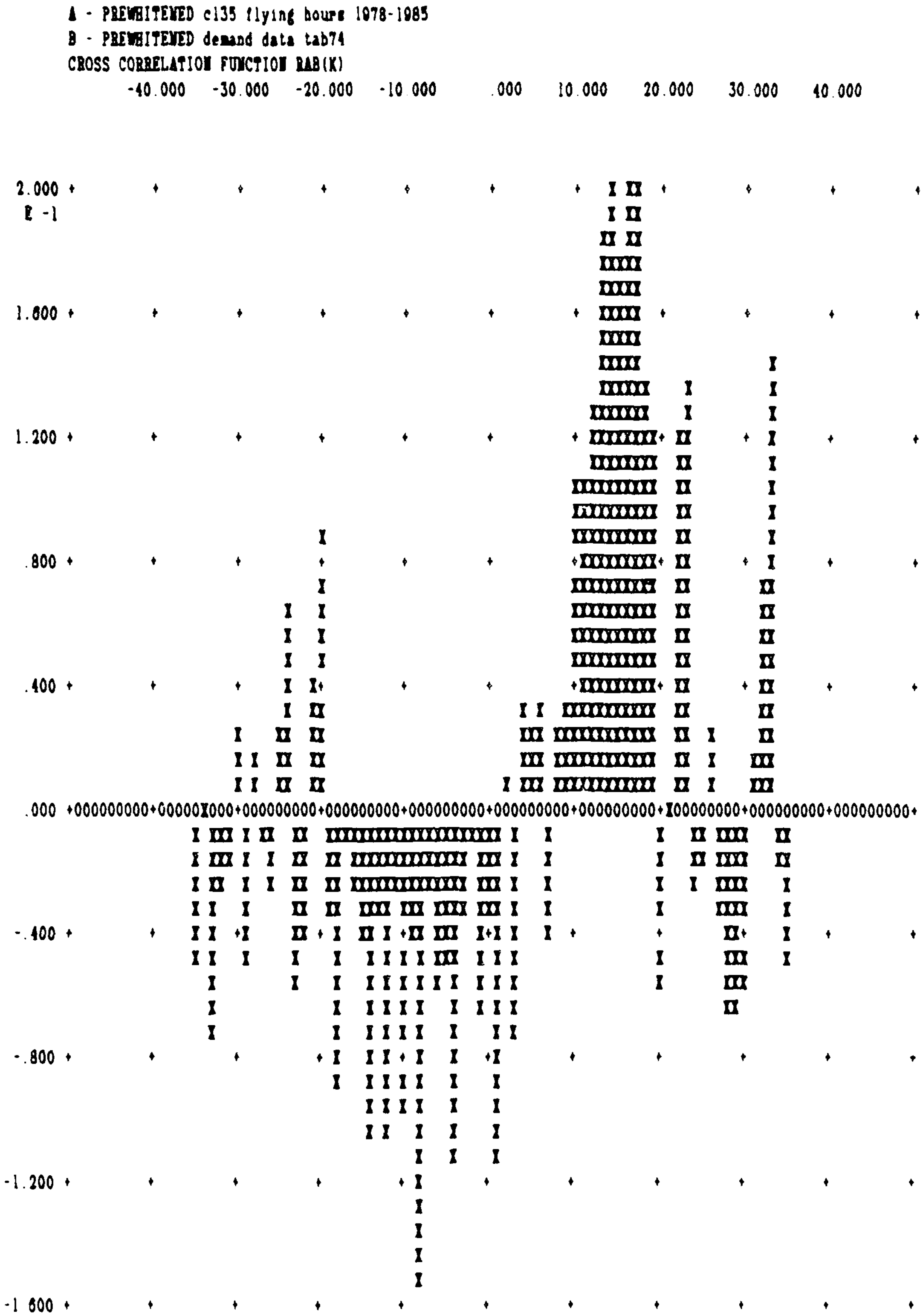

Figure 9. Plot of the Cross Correlations

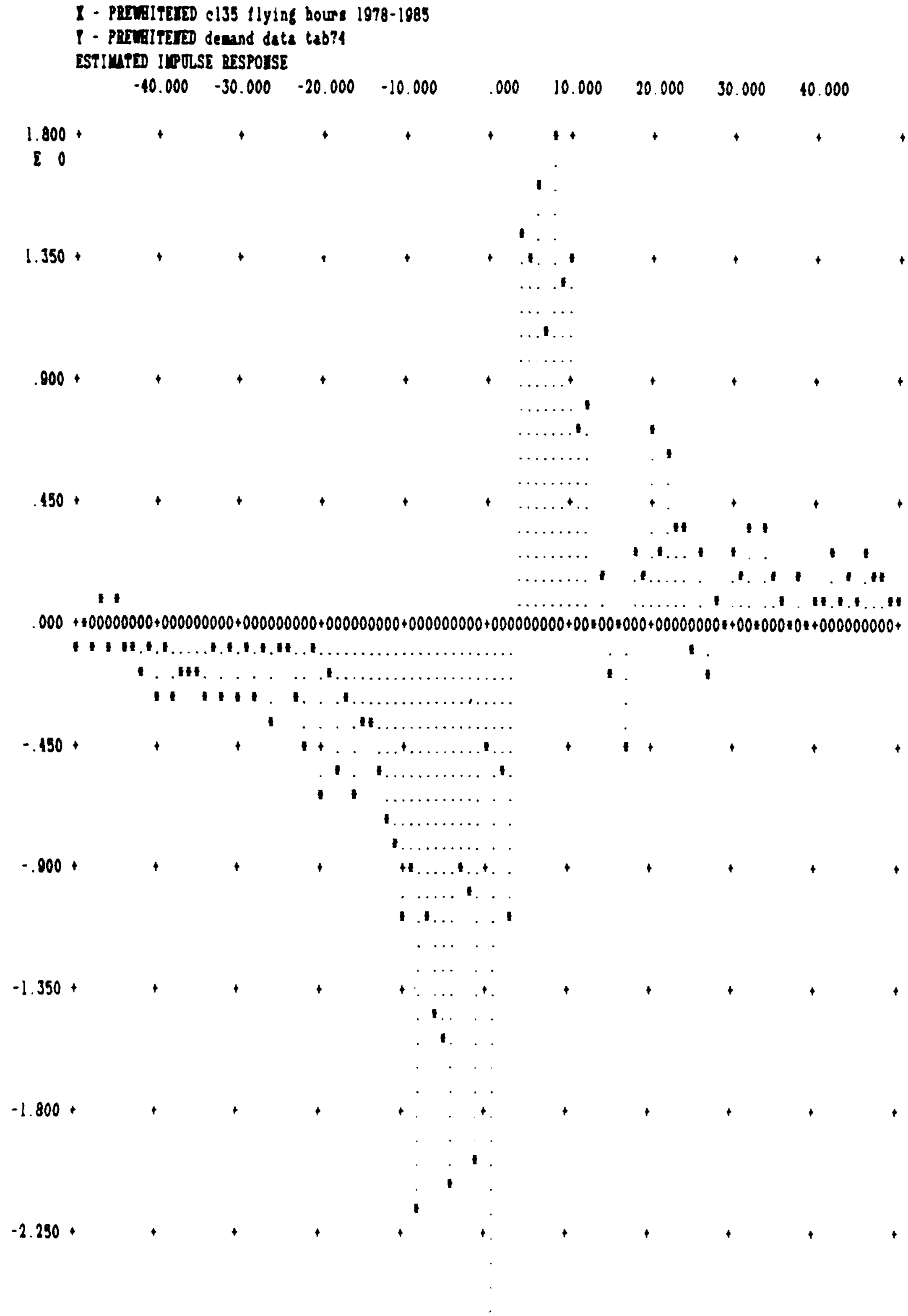

Figure 10. Plot of Estimated Impulse Response Weights

Table 5

Cross Correlation

Series 1 - Prewhitened C135 flying hours 1978-1985
Series 2 - Prewhitened demand data for TAB74

Number of Lags on Series 1	Cross Correlations	Number of Lags on Series 2	Cross Correlations
0	-.035	0	-.035
1	-.109	1	-.067
2	.005	2	-.010
3	-.071	3	-.034
4	.028	4	-.116
5	.027	5	-.046

The large spike at zero in Figure 9 indicates v_0 is not zero which in turn indicates b = 0 for the TAB74 model. When b = 0, there is no time period delay for the effect of X_t (flying hours) on Y_t. Since there is no apparent pattern in the right hand side correlation in Figure 9, r = 0. For the model, s was also determined to = 0.

Once r, s, and b are estimated, the s's and w's in Eq (5) are determined with a series of equations for the impulse response functions (3:383). For this model, only the w_0 value is present since b = 0. The value for w_0 was estimated to equal -.847 from the estimated impulse response weights in Table 4. All other w_s values are zero so each term with a w_s value other than w_0 drops out of Eq (5). The X_{t-b} terms in Eq (5) reduce to

$-.867 \ln X_t$. Since $r = 0$, the left hand side of Eq (5) reduces to Y_t.

Second, a TIMES test run is done using the s's and v's as input and output lag values for the transfer function model. The test run output shows whether or not noise parameters are necessary. Noise parameters are needed if more than white noise remains in the model (significant spikes appear in the noise output). The TAB74 test run ACF and PACF had significant spikes at lags 1 and 2. To prewhiten the noise function an AR and MA term were added to the equation as noise parameters. The final model with noise parameters included, next goes through diagnostic checking for validity.

The diagnostic checks resulted in acceptance of the model for the noise function. The residual ACF and PACF showed no significant spikes. The Chi-square value of 24 at 33 degrees of freedom was acceptable. The residual mean square was low at .56. Figures 11 and 12 show both the Cumulative Periodogram and Histogram of residuals are good. The input lag and noise parameter values are shown in Figure 13. For the TAB74 model, the noise portion of Eq (5) becomes:

$$N_t = -.254N_{t-1} + .157N_{t-2} + a_t \qquad (6)$$

where:

a_t = random error term.

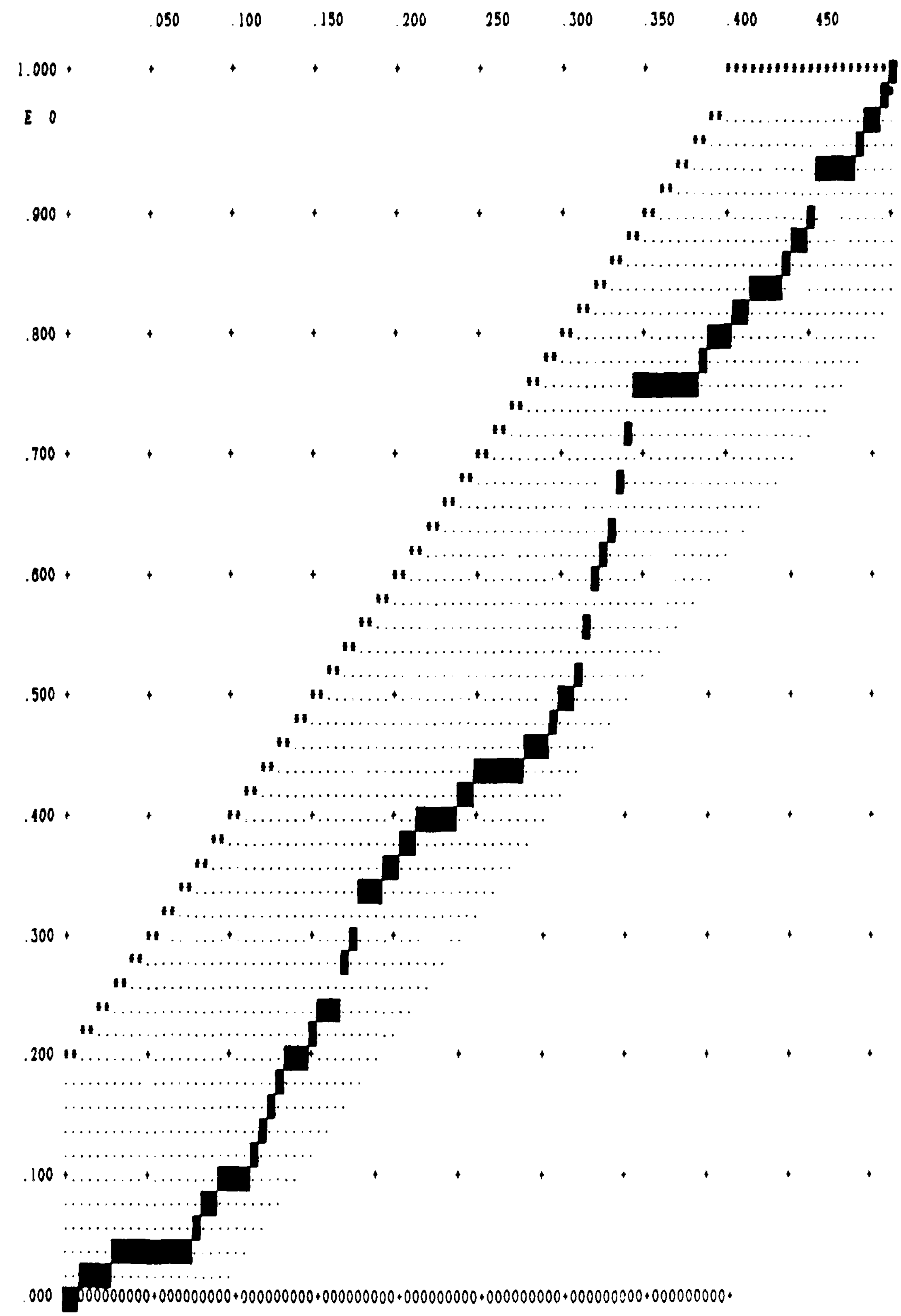

Figure 11. Transfer Function Cumulative Periodogram

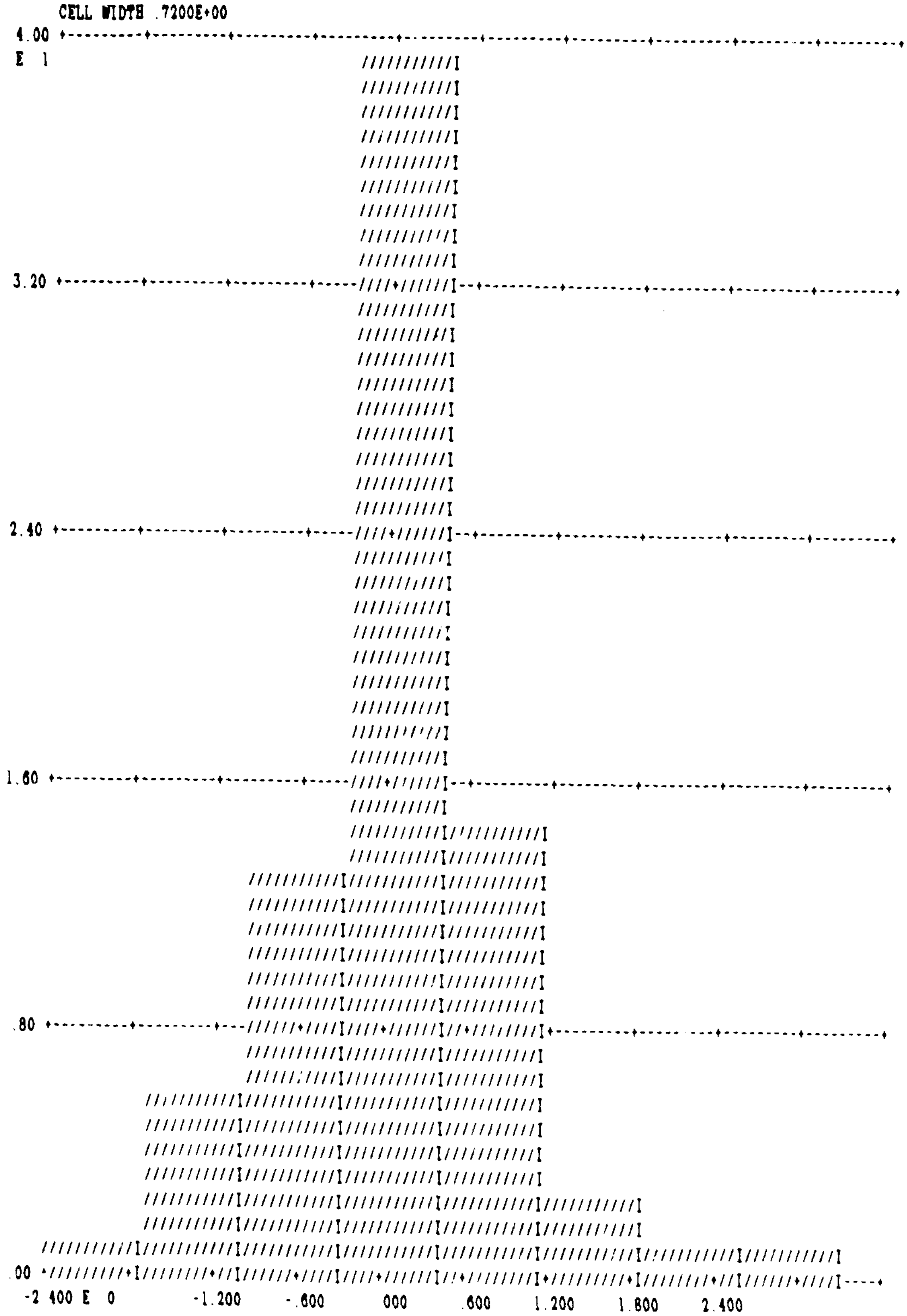

Figure 12. Transfer Function Histogram of Residuals

SUMMARY OF MODEL 1

DATA - X = c135 flying hours 1978-1985 96 OBSERVATIONS
Y = demand data tab74

DIFFERENCING ON Y - 1 OF ORDER 1

DIFFERENCING ON X - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.25443E+00	-.46367E+00	-.45181E-01
2	MOVING AVERAGE 1	2	.15681E+00	-.56972E-01	.37059E+00

TRANSFER FUNCTION PARAMETERS

3	INPUT LAG 1	0	-.64132E+00	-.24029E+01	.11202E+01

OPTIMUM VALUE OF B IS 0

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.51012E+02	91 D.F.	RESIDUAL MEAN SQUARE	.56057E+00
NUMBER OF RESIDUALS	94		RESIDUAL STANDARD ERROR	.74871E+00

Figure 13. Transfer Function Model Parameters

The entire equation for the transfer function with parameter values included for the TAB74 spare is:

$$Y_t = -.867LnX_{t-1} - .615LnX_{t-12} + .61LnX_{t-13} + .681e_{t-1} + .303e_{t-4} - .229e_{t-5} + e_t - .254N_{t-1} + .157N_{t-2} + a_t \quad (7)$$

Each of the other nine spares models were processed through the same steps of identification, estimation, and diagnostic checking to develop a model for forecasting demand. The plots and parameter values for the remaining nine spares are in Appendix B. The equations for the nine models are listed below:

(1) FAIR01

$$Y_t = -.33LnX_{t-1} - .224LnX_{t-14} + .264e_{t-1} + .132e_{t-4} - .106e_{t-5} - .32e_t - .3N_{t-1} + .7N_{t-6} + a_t$$

(2) ASSY31

$$Y_t = 3.96LnX_{t-1} + 2.69LnX_{t-12} - 2.69LnX_{t-13} - 3.16e_{t-1} - 1.58e_{t-4} + 1.27e_{t-5} + 3.96e_t + .18N_{t-3} + .7N_{t-6} + a_t$$

(3) FRAME53

$$Y_t = -.249LnX_{t-1} - .169LnX_{t-12} + .169LnX_{t-13}$$

$$+ .199e_{t-1} + .10e_{t-4} - .08e_{t-5}$$

$$- .249e_t + .02N_{t-2} + a_t$$

(4) TAIL84 - NO NOISE PARAMETERS NEEDED

$$Y_t = -2.0LnX_{t-2} - 1.36LnX_{t-13} + 1.36LnX_{t-14}$$

$$+ 1.6e_{t-1} + .8e_{t-4} - .64e_{t-5} - 2e_t + a_t$$

(5) COWL83

$$Y_t = -.272LnX_{t-1} - .185LnX_{t-12} - .185X_{t-13}$$

$$+ .218e_{t-1} + .1e_{t-14} - .087e_{t-5} - .27e_t$$

$$- .127N_{t-1} - .128N_{t-2} - .174N_{t-3} + a_t$$

(6) SLVE85

$$Y_t = .132LnX_{t-1} - .661LnX_{t-2} + .09LnX_{t-12}$$

$$- .54LnX_{t-13} + .45LnX_{t-14} - .771e_{t-1}$$

$$+ .132e_t + .53e_{t-2} - .06e_{t-4} + .32e_{t-5}$$

$$- .21e_{t-6} - .063N_{t-1} + .057N_{t-2}$$

$$- .3N_{t-3} + a_t$$

(7) ASSY32

$$Y_t = 6.33LnX_{t-1} + 4.3LnX_{t-12} - 4.3LnX_{t-13}$$

$$- 5.1e_{t-1} - 2.5e_{t-4} + 2e_{t-5}$$

$$+ 6.33e_t - .38eN_{n-3} + a_t$$

(8) ASSY33 - NO NOISE PARAMETERS NEEDED

$$Y_t = 1.2LnX_{t-1} + .82LnX_{t-12} - .82LnX_{t-13}$$

$$- .97e_{t-1} - .48e_{t-4} + .39e_{t-5} + 1.2e_t + a_t$$

(9) FORK35

$$Y_t = -.01LnX_{t-4} + .61LnX_{t-6} + 1.4LnX_{t-7}$$

$$- .007LnX_{t-16} + .42LnX_{t-17} + .56LnX_{t-18}$$

$$- .97LnX_{t-19} + .01e_t + .62e_{t-1}$$

$$+ .93e_{t-2} - 1.1e_{t-4} -.24e_{t-5} - .37e_{t-6}$$

$$+ .45e_{t-7} + .17N_{t-1} + .32N_{t-6} + a_t$$

These ten transfer function models forecast spares demand for the Jan - Mar 1986 quarter. Results follow.

Multivariate Forecasting Results. Table 6 shows the Box-Jenkins transfer function models ranged widely in their accuracy for predicting quarterly demand. Four of the models had less than a 10% mean absolute percentage error from the actual demand. Each of the four (TAB74, TAIL84, ASSY32, and ASSY33) overpredicted the demand versus underestimating it. The ASSY31 model had a 10.4% error and also overestimated. The other five models ranged in accuracy error from 17.6% to 50% and in two of the five instances, the model underestimated demand.

The next models analyzed are the ten Box-Jenkins univariate models which use only past demand and the within relationships to estimate future demand. The steps of identification, estimation, and diagnostic checking are shown for the TAB74 model followed by the formulae and forecasts for the ten spares models.

Table 6

Transfer Function Models' Forecasting Results

NSN	Actual Value	Forecast	MAPE(%)
FAIR01	77	99	28.6
ASSY31	230	254	10.4
TAB74	26	27	3.8
FRAME53	34	40	17.6
TAIL84	9	9	0
COWL83	10	5	50
SLVE85	13	9	30.8
ASSY32	262	279	6.5
ASSY33	170	174	2.4
FORK35	17	21	23.5

Univariate Model Formulation

Univariate Model Identification. Each of the ten spares models were built using the same Box-Jenkins steps as those used to form the univariate flying hours model. The first steps in building the univariate model TAB74 were to plot the original data and run a TIMES identification run to study the ACF and PACF and to compare the Chi-square values for the original data and the first and second difference. The results indicate whether the data is stationary or not.

The plot of the original data (Figure 14) did not have a constant mean indicating the possibility of non-stationarity. The ACF plot did not die out quickly which also supported non-stationarity. The third indicator of non-stationarity was the Chi-square value. The Chi-square value for the first differenced data was the smallest indicating first differencing the data would produce the most stationary data.

The TAB74 data was first differenced. The ACF and PACF showed significant spikes at lags 1, 4, 6, and 7. The plot of the differenced data showed a much more stationary pattern with a constant mean (Figure 15). Based on the ACF and PACF, possible models to try were the ARIMA's (1,1,1), (0,1,2), and (0,1,3).

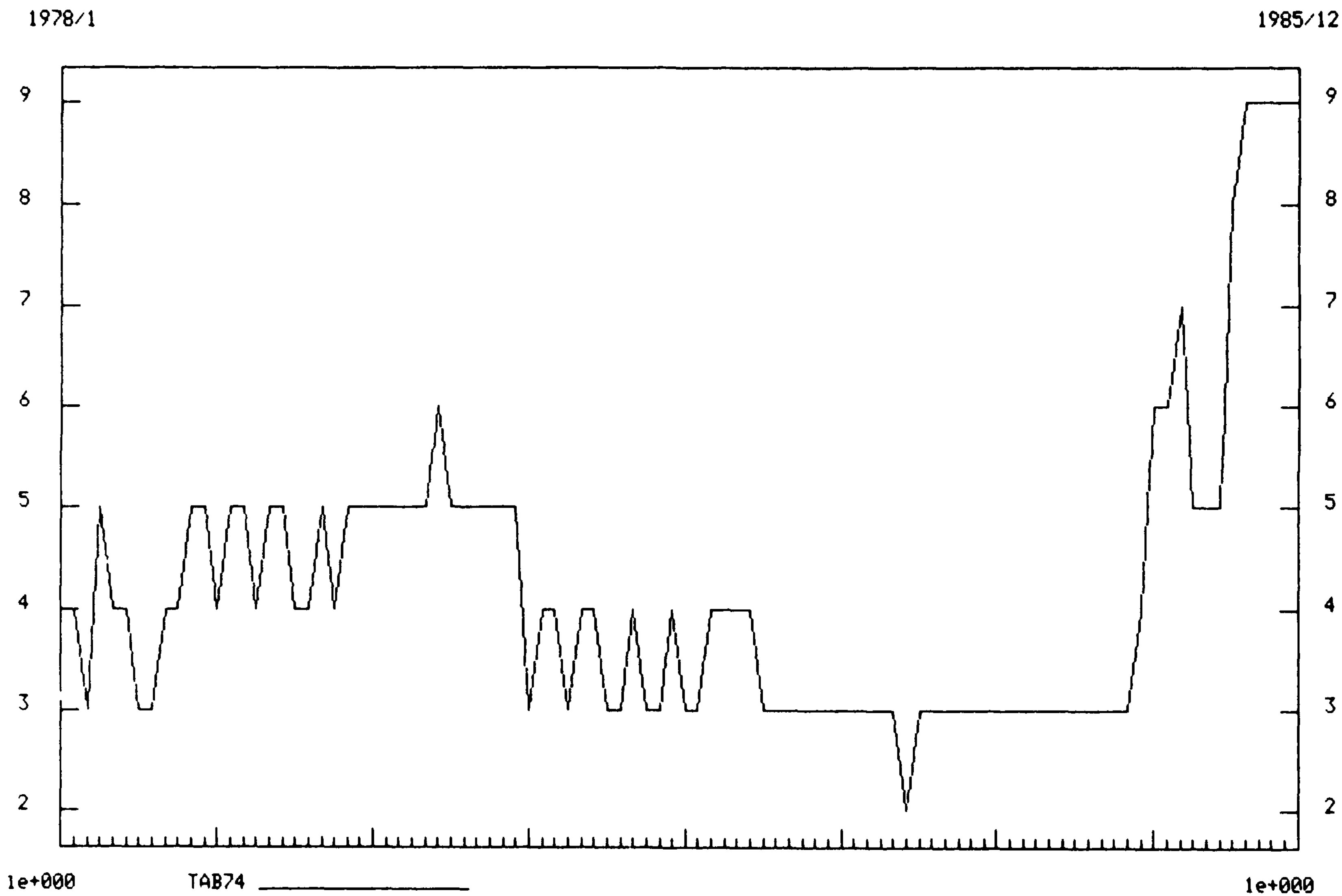

Figure 14. TAB74 Original Data Plot

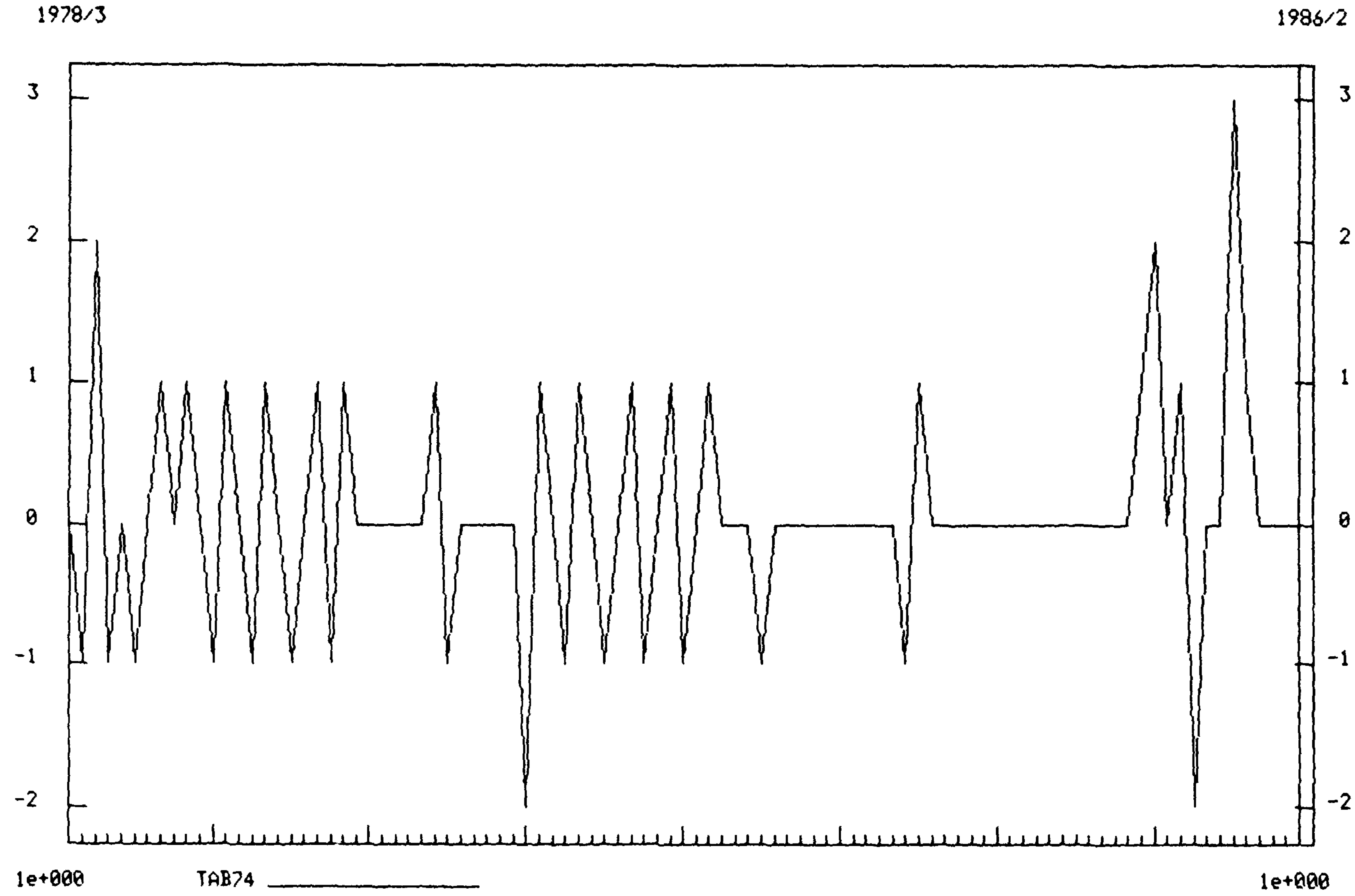

Figure 15. TAB74 First Differenced Data

Univariate Model Estimation and Diagnostics. A comparison of each of the three ARIMA models resulted in the ARIMA (0,1,3) having the smallest Chi-square value of 14.0 at 33 degrees of freedom and the smallest residual mean square of 0.464 (Figure 16). To confirm the ARIMA (0,1,3) was valid, diagnostic checks were done. The ACF and PACF each had no significant spikes remaining. The Chi-square value of 14 at 33 degrees of freedom was well within the standard. The Cumulative Periodogram, Histogram of Residuals, and Power Spectrum all had positive results (see Figures 17, 18, and 19). The parameter values for the chosen ARIMA (0,1,3) are shown in Figure 16. The equation with parameter values is:

$$Y_t = Y_{t-1} + e_t - .349e_{t-1} - .103e_{t-4} + .425e_{t-6} \qquad (8)$$

The output for each of the nine Box-Jenkins univariate models is in Appendix C. The nine equations with parameter values for the univariate models are shown:

(1) FAIR01 - ARIMA (2,1,2)

$$Y_t = .804Y_{t-1} - .106Y_{t-2} - .136Y_{t-3}$$
$$+ e_t - .898e_{t-4} + .59e_{t-6}$$

SUMMARY OF MODEL 1

DATA - Z = demand data 96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	MOVING AVERAGE 1	1	.34861E+00	.16856E+00	.52866E+00
2	MOVING AVERAGE 1	4	.10250E+00	-.80312E-01	.28532E+00
3	MOVING AVERAGE 1	6	-.42476E+00	-.60860E+00	-.24093E+00

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.42671E+02	92 D.F.	RESIDUAL MEAN SQUARE	.46382E+00
NUMBER OF RESIDUALS	95		RESIDUAL STANDARD ERROR	.68104E+00

Figure 16. TAB74 Parameter Values - Univariate Model

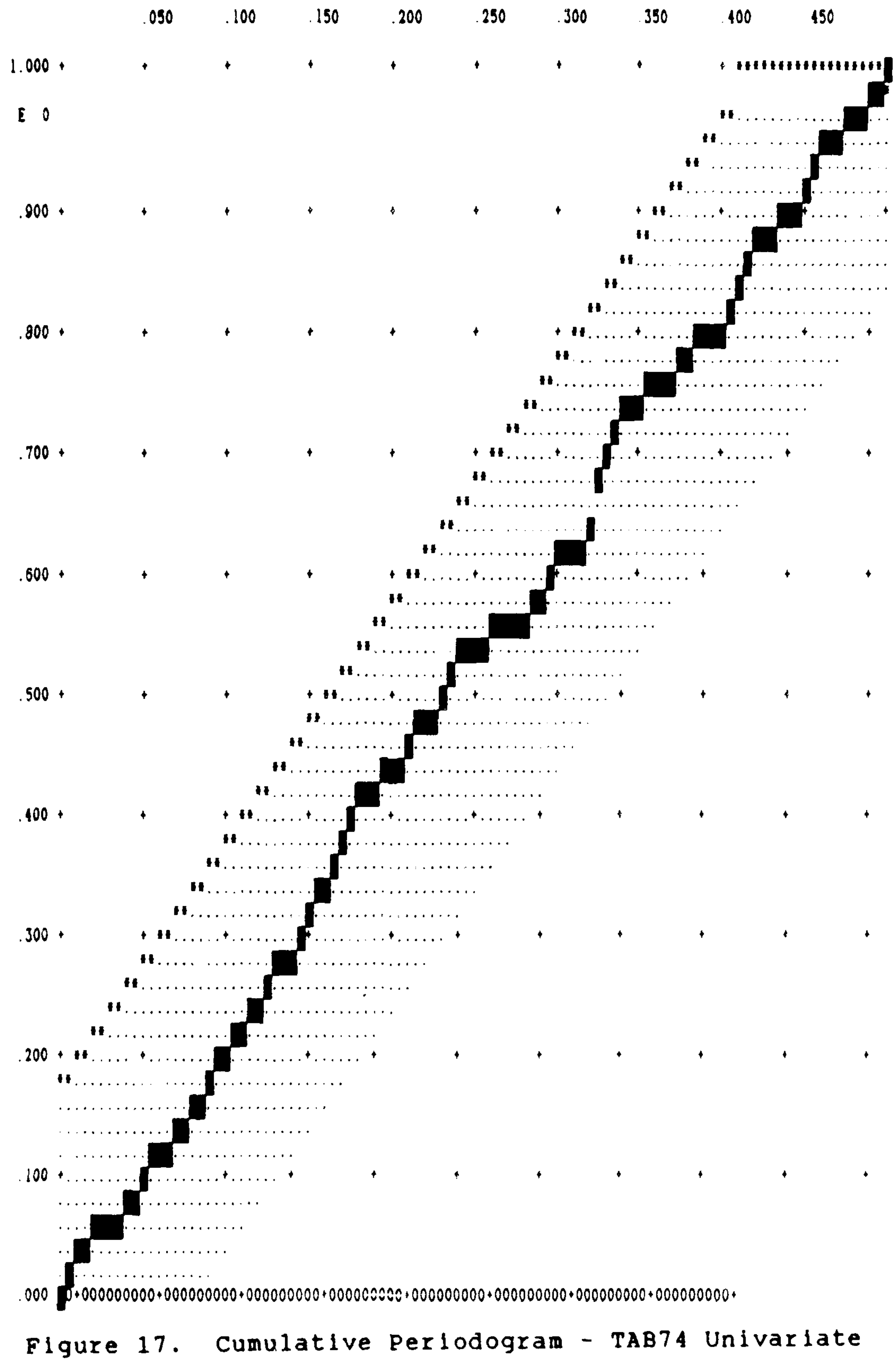

Figure 17. Cumulative Periodogram - TAB74 Univariate

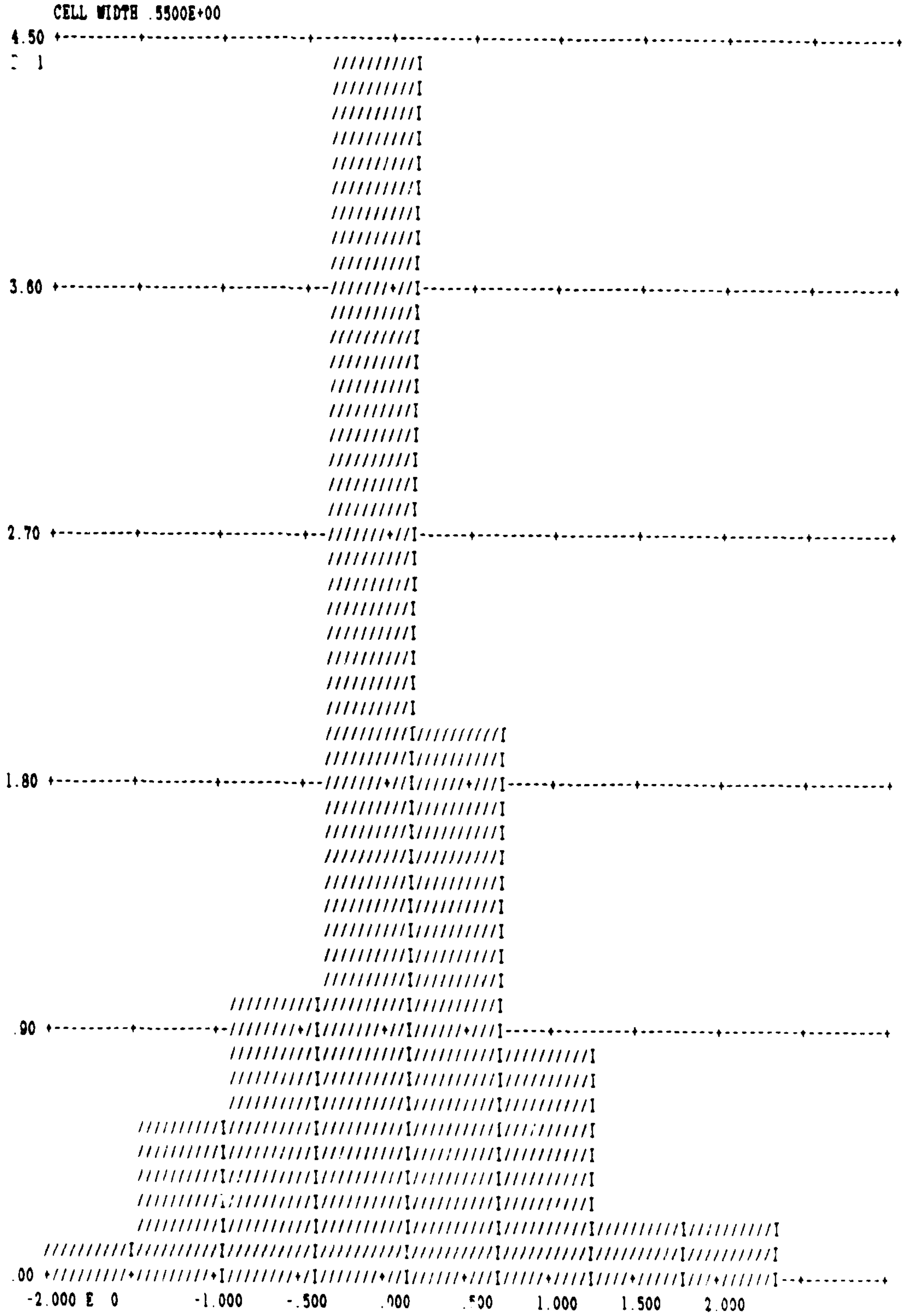

Figure 18. Histogram of Residuals - TAB74 Univariate

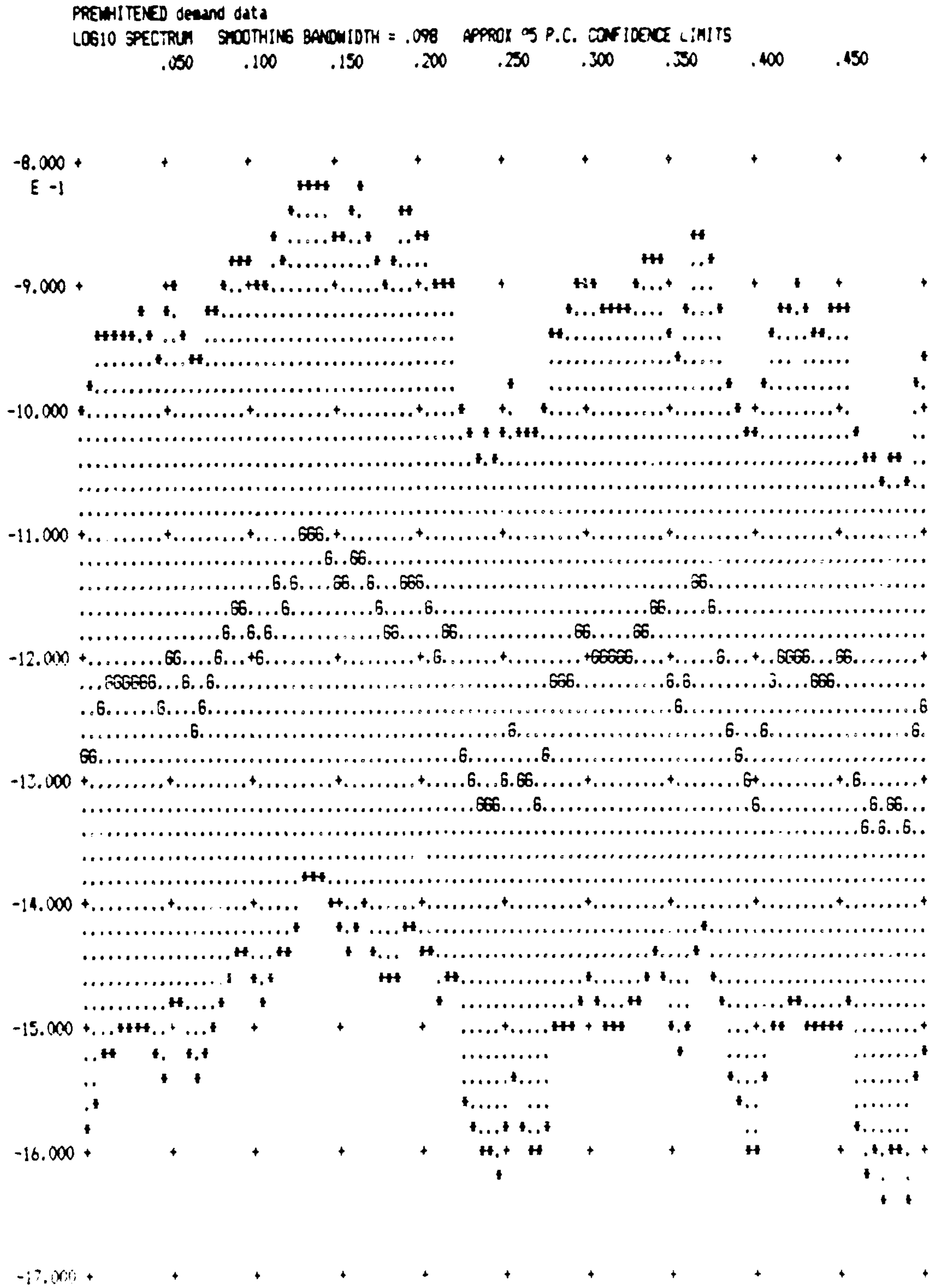

Figure 19. Power Spectrum - TAB74 Univariate

(2) ASSY31 - ARIMA (0,1,2)

$$Y_t = Y_{t-1} + e_t + .197e_{t-3} + .321e_{t-6}$$

(3) FRAME53 - ARIMA (0,1,2)

$$Y_t = Y_{t-1} + e_t - .146e_{t-1} - .135e_{t-5}$$

(4) TAIL84 - ARIMA (0,1,3)

$$Y_t = Y_{t-1} + e_t - .077e_{t-1} + .133e_{t-3} - .237e_{t-5}$$

(5) SLVE85 - ARIMA (2,1,2)

$$Y_t = .56Y_{t-1} - .34Y_{t-2} - .329Y_{t-3}$$

$$+ .32Y_{t-4} + e_t - .83e_{t-2} + .49e_{t-6}$$

(6) COWL83 - ARIMA (0,1,1)

$$Y_t = .89Y_{t-1} - .126Y_{t-2} - .116Y_{t-3}$$

$$- .126Y_{t-3} + e_t + .427e_{t-3} + .114e_{t-6}$$

(7) ASSY32 - ARIMA (0,1,1)

$$Y_t = Y_{t-1} + e_t + .383e_{t-3}$$

(8) ASSY33 - ARIMA (0,1,1)

$$Y_t = Y_{t-1} + e_t + .413e_{t-6}$$

(9) FORK35 - ARIMA (2,1,3)

$$Y_t = Y_{t-1} + .832Y_{t-3} - .21\,Y_{t-4} + .143Y_{t-5}$$
$$+ e_t + .163e_{t-1} - .112e_{t-2} + .282e_{t-6}$$

Each of the univariate models was used to forecast demand for the Jan - Mar 1986 quarter. These univariate models were developed using demand relationships to predict demand. The previous multivariate models used the relationships among and between flying hours and demand to predict future demand. Table 7 shows the results of the Box-Jenkins univariate models' results for the ten spares forecasts.

The results of the forecasts ranged from three models (ASSY31, COWL83, and SLVE85) predicting the exact demand while the other seven models ranged in mean absolute percentage error from 11.1% to 19.5%. Note the range of error is smaller than the range for the transfer function models', but then, the transfer function models had five with less than a 10% error. In each univariate model, the forecast was either exact or an overestimation. For aircraft recoverable spares,

Table 7

Univariate Models' Forecasting Results

NSN	Actual Value	Forecast	MAPE(%)
FAIR01	77	92	19.5
ASSY31	230	231	0
TAB74	26	30	15.4
FRAME53	34	40	17.6
TAIL84	9	10	11.1
COWL83	10	10	0
SLVE85	13	13	0
ASSY32	262	293	11.8
ASSY33	170	194	14.1
FORK35	17	20	17.6

it is more mission essential to overestimate versus underestimate future requirements. The next section reviews the forecasting results found using simple exponential smoothing on FORECAST MASTER software.

Simple Exponential Smoothing

The ten spares demand data sets were run on FORECAST MASTER software using an a = 0.4 value for each run. This value was recommended by Craig Sherbrooke in his study discussed in Chapter II. The results of the forecasts for the Jan - Mar 1986 quarter are in Table 8. Note that three models (TAIL84, ASSY3_, and ASSY33) forecast exact demand. Five of the other models were within 10% of the actual value. The other two models (FRAME53 and FORK35) had errors of 14.7% and 41.2%; both were overestimations of demand.

Table 8

Simple Exponential Smoothing Models' Forecasting Results

NSN	Actual Value	Forecast	MAPE(%)
FAIR01	77	81	5.2
ASSY31	230	212	7.8
TAB74	26	27	3.8
FRAME53	34	39	14.7
TAIL84	9	9	0
COWL83	10	11	10
SLVE85	13	12	7.7
ASSY32	262	263	0
ASSY33	170	170	0
FORK35	17	24	41.2

Answers for Investigative Questions

In Chapter I, questions were asked to aid in the analysis and development of time series models to forecast C-135 recoverable spares. Below are the answers and findings for the questions.

(1) What type of relationship exists between C-135 flying hours and demand in the transfer function models?

In each of the ten multivariate transfer function models, the cross correlation values were not as high as expected. Low cross correlation values indicate the relationship between flying hours and demand for the C-135 data is not strong. Two conditions which are necessary for a transfer function to work are, the impulse response weights must converge and second, some small incremantal change in X_t (flying hours) results in a small incremental change in Y_t (demand) (4).

In the majority of the transfer function models, the spares demand was related to flying hours 1, 12, and 13 time periods prior. The transfer function equations shown earlier in this chapter show the actual prior time periods in which demand is related to flying hours for each individual model. When the flying hours data was prewhitened, there was no trend in the data but a seasonal component existed at time periods of 4 and 12.

(2) and (3) Which forecasting techniques best modelled the data and produced the most accurate results?

Each of the three types of models (Box-Jenkins multivariate, Box-Jenkins univariate, and simple exponential smoothing), modelled the data accurately since each of the three types of models forecast one quarter of demand for the spares with accurate results. The objective in developing the Box-Jenkins models was to build models which "fit" the actual data versus building to obtain "forecast" accuracy. The final section compares the mean absolute percentage error for each of the ten spares using the three types of models.

Table 9 is a comparison of the mean absolute percentage errors for the ten spares. The Box-Jenkins transfer fu... and univariate demand models did well but the exponential smoothing with a = 0.4 had the lowest average percentage error for the ten different spares.

Table 9

Comparison of Forecasting Results

NSN	Transfer Func. MAPE(%)	Univariate MAPE(%)	Simple Exp. MAPE(%)
FAIR01	28.6	19.5	5.2
ASSY31	10.4	0	7.8
TAB74	3.8	15.4	3.8
FRAME53	17.6	17.6	14.7
TAIL84	0	11.1	0
COWL83	50	0	10
SLVE85	30.8	0	7.7
ASSY32	6.5	11.8	0
ASSY33	2.4	14.1	0
FORK35	23.5	17.6	41.2
AVERAGE MAPE:	17.4	11.0	9.0

V. Conclusions and Recommendations

For the last several years, emphasis has been placed on finding forecasting techniques to improve on the past underestimations of aircraft recoverable spares. Two views of approaching forecasting spares which were discussed in the Chapter II literature review are to use time series techniques or, techniques such as exponential smoothing. The purpose of this research was to compare Box-Jenkins time series techniques to simple exponential smoothing with C-135 demand and flying hours data. The Box-Jenkins multivariate/transfer function models use the relationship of flying hours and demand to forecast future demand. The Box-Jenkins univariate models used past demand and it's relationship with time and past demand to forecast future demand. Simple exponential smoothing used past demand data with more emphasis placed on recent demand to forecast future demand. Chapter IV provided a comparison of the results of the forecasts for each of the three methods.

Findings

Key findings of the research are summarized below:

- Low cross correlation values during transfer function model development indicated flying hours were not as highly correlated with demand as expected.

- The average mean absolute percentage error for the ten spares was 17.4% when using the transfer function models.

- Two of the ten spares' demand were underestimated when using the transfer function models.

- The average mean absolute percentage error for the ten spares was 11% for the Box-Jenkins univariate models.
- The univariate models did not underestimate demand.
- The average mean absolute percentage error for the ten spares was 9% using simple exponential smoothing.
- The simple exponential smoothing models underestimated demand for two spares' forecasts.

Research Limitations

Box-Jenkins time series analysis requires at least forty and preferably 100 data values. Because of this, only one quarter's demand was withheld to take advantage of Box-Jenkins' powerful techniques of developing models which predict accurate mid-to-long term forecasts. Simple exponential smoothing is advantageous for short term (1-3 months) forecasting. Therefore, only having one quarter of data to compare actual and forecast values favored exponential smoothing.

Conclusions

This research determined Box-Jenkins techniques can be used to accurately forecast future aircraft recoverable spares. Previous theses built transfer function models but did not use the models to forecast. Numerical results show the transfer function models which use flying hours to forecast demand, may be more complex than needed since both the Box-Jenkins univariate and simple exponential smoothing models produced better results (11% and 9% versus 17%) for one quarter when only using past demand. One reason for the

transfer function models not forecasting as well is the C-135 flying hours were not as highly correlated to demand as expected. It should be noted though, that Box-Jenkins techniques are used for mid-to-long term (1 - 2 years) forecasting while simple exponential smoothing is short term (1 - 3 months). Due to data constraints, only one quarter of demand was forecast and compared to actual; this favors simple exponential smoothing. The accuracy of simple exponential smoothing with a = 0.4, as Sherbrooke recommended, shows it may not be necessary to remove "within" and "between" relationships in the data to forecast accurately.

The results of these forecasting models impact the AF/DOD budget process since the determination of spares requirements is usually made 2 - 3 years ahead of actual support arriving. Box-Jenkins techniques are powerful enough to forecast 1 - 2 years ahead for demand. In cases where item managers need short term forecasts, this research indicates simple exponential smoothing would be very effective. Depending on the time horizon of the forecast needed and the amount of data available, both the TIMES and FORECAST MASTER software are available for Air Force use. TIMES was originally designed for Air Force use on mainframe computers which compile Fortran. It has recently been converted for personal computer use at AFIT. FORECAST MASTER software is personal computer software which is very user friendly and capable of doing both

Box-Jenkins and simple exponential smoothing models as well as many others.

One other conclusion of this research is that Air Force data collection and storage is not condusive to using Box-Jenkins analysis since a large number of data points are needed and the majority of data is stored as quarterly which gives four points per year of data. Capabilities of today's personal computers and mainframes allow storage of vast amounts of data which fifteen years ago wouldn't fit on a mainframe computer. Whenever possible, data should be stored at a minimum of monthly, which opens the doors to powerful techniques such as Box-Jenkins. Incomplete data storage also lessens the capability of getting true and accurate results based on past data if there are excessive gaps in the data.

Recommendations

The models used in this thesis produced accurate results, so additional research should be accomplished to compare the mid-to-long term forecasting of the three techniques since only short term was tested. In studying Box-Jenkins time series techniques, it is also recommended that:

- The flying-hours-demand relationship be studied for other weapon systems and their spares.

- Multivariate models be further tested which also take into account demand relationships with variables such as number of take-offs and/or landings, number of sorties, and age of the aircraft fleet.

- Studies be accomplished which explore combining spares based on similar stock class or end item use to test whether or not aggregate forecasting is possible.

Appendix A: Flying Hour and Spares Demand Data

Table A1

Monthly Flying Hours Data

Date	Flying Hours	Date	Flying Hours	Date	Flying Hours
7801	21045	8108	20516	8503	22408
7802	21718	8109	23877	8504	22578
7803	24259	8110	23592	8505	22338
7804	22467	8111	21251	8506	21451
7805	23068	8112	19078	8507	21991
7806	22734	8201	19643	8508	22759
7807	21738	8202	20939	8509	21499
7808	24310	8203	23821	8510	25407
7809	24361	8204	22718	8511	20361
7810	24623	8205	21688	8512	18895
7811	22772	8206	22932		
7812	18724	8207	22430		
7901	22055	8208	21308		
7902	21126	8209	20719		
7903	24432	8210	22993		
7904	23172	8211	21484		
7905	23995	8212	19332		
7906	22588	8301	20645		
7907	21846	8302	20358		
7908	24984	8303	23593		
7909	21511	8304	22420		
7910	24319	8305	21834		
7911	21817	8306	22266		
7912	17587	8307	20418		
8001	21066	8308	22498		
8002	20539	8309	20978		
8003	21454	8310	24294		
8004	22827	8311	20942		
8005	22466	8312	18531		
8006	21855	8401	21017		
8007	22179	8402	20516		
8008	21009	8403	22794		
8009	19514	8404	23141		
8010	23817	8405	22251		
8011	20728	8406	20903		
8012	19307	8407	21345		
8101	20981	8408	23393		
8102	21189	8409	21605		
8103	22703	8410	24985		
8104	22645	8411	21308		
8105	21340	8412	17854		
8106	21132	8501	21379		
8107	21298	8502	19842		

Table A2

Quarterly Demand Data

Date	FAIR01	ASSY31	TAB74	FRAME53	TAIL84
7803	23	40	11	12	21
7806	17	40	13	12	22
7809	19	43	10	10	24
7812	17	29	14	10	44
*7903	16	33	13	10	42
*7906	17	38	14	11	29
7909	18	42	13	11	23
*7912	17	41	14	10	30
8003	14	41	15	9	46
8006	18	46	16	13	43
*8009	19	49	15	13	27
8012	21	52	15	12	26
8103	17	78	11	20	9
*8106	19	85	11	21	9
8109	21	99	10	22	9
8112	20	100	10	25	7
8203	18	107	10	31	6
8206	17	122	12	32	7
8209	14	124	9	32	6
8212	21	138	9	34	7
8303	28	146	9	35	4
8306	28	137	8	45	3
8309	23	112	10	45	3
*8312	22	110	10	44	4
*8403	22	110	10	43	4
8406	23	109	10	42	5
8409	28	107	10	43	6
8412	28	97	11	38	7
8503	58	145	20	43	8
8506	52	154	15	50	9
8509	85	196	26	39	9
8512	81	219	27	37	9
**8603	77	230	26	34	9

* designates quarters with missing data
** designated quarter withheld to compare with forecasts

Table A2 (CON'T)

Quarterly Demand Data

Date	COWL83	SLVE85	ASSY32	ASSY33	FORK35
7803	53	9	39	44	42
7806	48	9	43	44	44
7809	40	10	52	52	43
7812	48	30	36	40	44
*7903	43	27	40	44	44
*7906	38	25	45	46	47
7909	34	22	52	51	47
*7912	40	33	50	50	44
8003	44	44	53	52	41
8006	43	46	64	59	43
*8009	40	40	70	62	42
8012	32	35	74	66	41
8103	27	24	94	83	45
*8106	21	18	109	90	43
8109	18	13	121	105	42
8112	17	12	117	111	40
8203	15	13	120	117	40
8206	15	11	134	142	43
8209	13	13	133	144	42
8212	11	13	144	155	40
8303	13	13	154	166	40
8306	15	16	141	158	33
8309	13	16	113	131	47
*8312	15	15	112	128	45
*8403	15	15	111	128	45
8406	16	14	109	126	48
8409	16	12	94	98	43
8412	15	12	88	88	42
8503	13	14	124	112	37
8506	12	11	130	[illegible]	40
8509	12	11	219	178	25
8512	11	12	280	171	22
**8603	10	13	262	170	17

*   designates quarters with missing data
** designated quarter withheld to compare with forecasts

Appendix B: Transfer Function Models

```
DATA - X = c135 flying hours 1978-1985                                       96 OBSERVATIONS
       Y = demand data

DIFFERENCING ON Y - 1 OF ORDER  1

DIFFERENCING ON X - 1 OF ORDER  1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

****************************************************************************************************

NOISE MODEL PARAMETERS

****************************************************************************************************

PARAMETER         PARAMETER           PARAMETER    ESTIMATED                95 PER CENT
 NUMBER             TYPE                ORDER        VALUE         LOWER LIMIT          UPPER LIMIT

****************************************************************************************************

   1           AUTOREGRESSIVE 1           1        -.10936E+00       -.27947E+00          .60751E 01

   2           AUTOREGRESSIVE 1           6         .78101E+00        .56125E+00          .10008E+01

****************************************************************************************************

TRANSFER FUNCTION PARAMETERS

****************************************************************************************************

   3           INPUT LAG 1                0        -.33428E+00       -.29797E+01          .23111E+01

****************************************************************************************************

OPTIMUM VALUE OF B IS  0

****************************************************************************************************

OTHER INFORMATION AND RESULTS

****************************************************************************************************

RESIDUAL SUM OF SQUARES       .18636E+03     86 D.F.         RESIDUAL MEAN SQUARE            .21670E+01

NUMBER OF RESIDUALS                   89                     RESIDUAL STANDARD ERROR         .14721E+01
```

Figure B1. FAIR01 Transfer Function Parameter Values

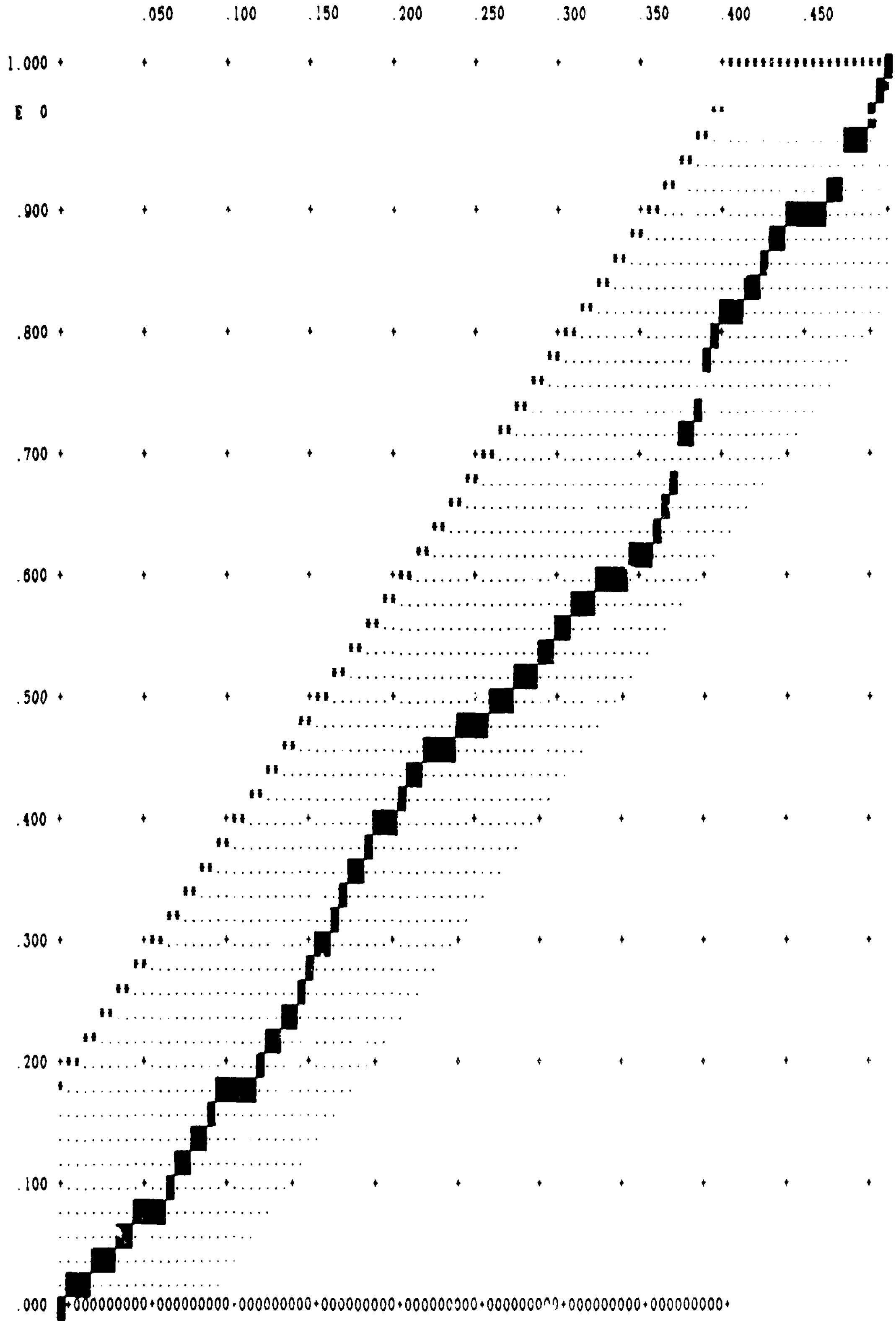

Figure B2. FAIR01 Transfer Function Cumulative Periodogram

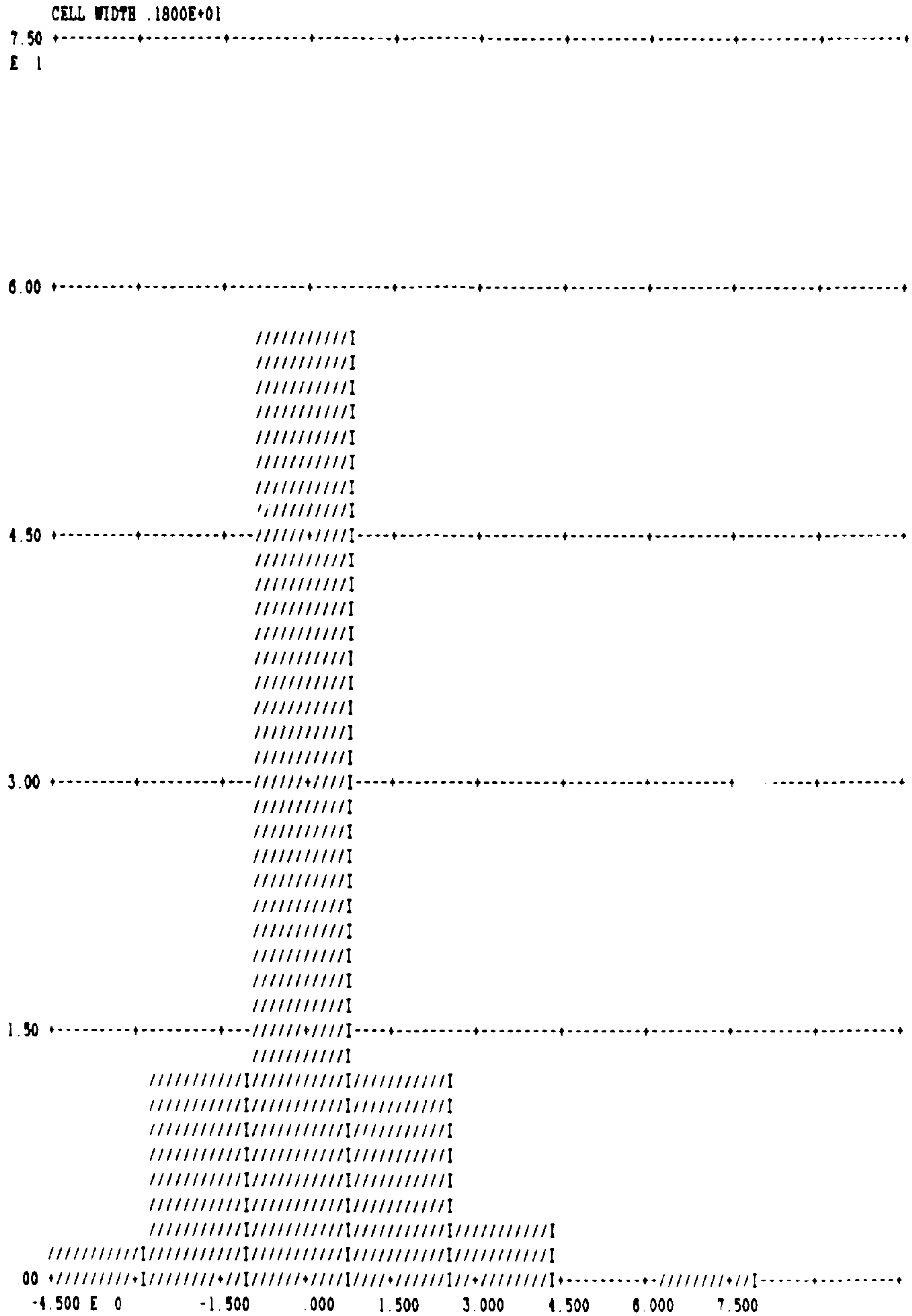

Figure B3. FAIR01 Transfer Function Histogram of Residuals

SUMMARY OF MODEL 1

DATA - X = c135 flying hours 1978-1985 — 96 OBSERVATIONS
Y = demand data assy31

DIFFERENCING ON Y - 1 OF ORDER 1

DIFFERENCING ON X - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	3	.18896E+00	-.16013E-01	.39393E+00
2	AUTOREGRESSIVE 1	6	.41729E+00	.18198E+00	.65260E+00

TRANSFER FUNCTION PARAMETERS

3	INPUT LAG 1	0	.39627E+01	-.11804E+01	.91058E+01

OPTIMUM VALUE OF B IS 0

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.56901E+03	86 D.F.	RESIDUAL MEAN SQUARE	.66164E+01
NUMBER OF RESIDUALS	89		RESIDUAL STANDARD ERROR	25722E+01

Figure B4. ASSY31 Transfer Function Parameter Values

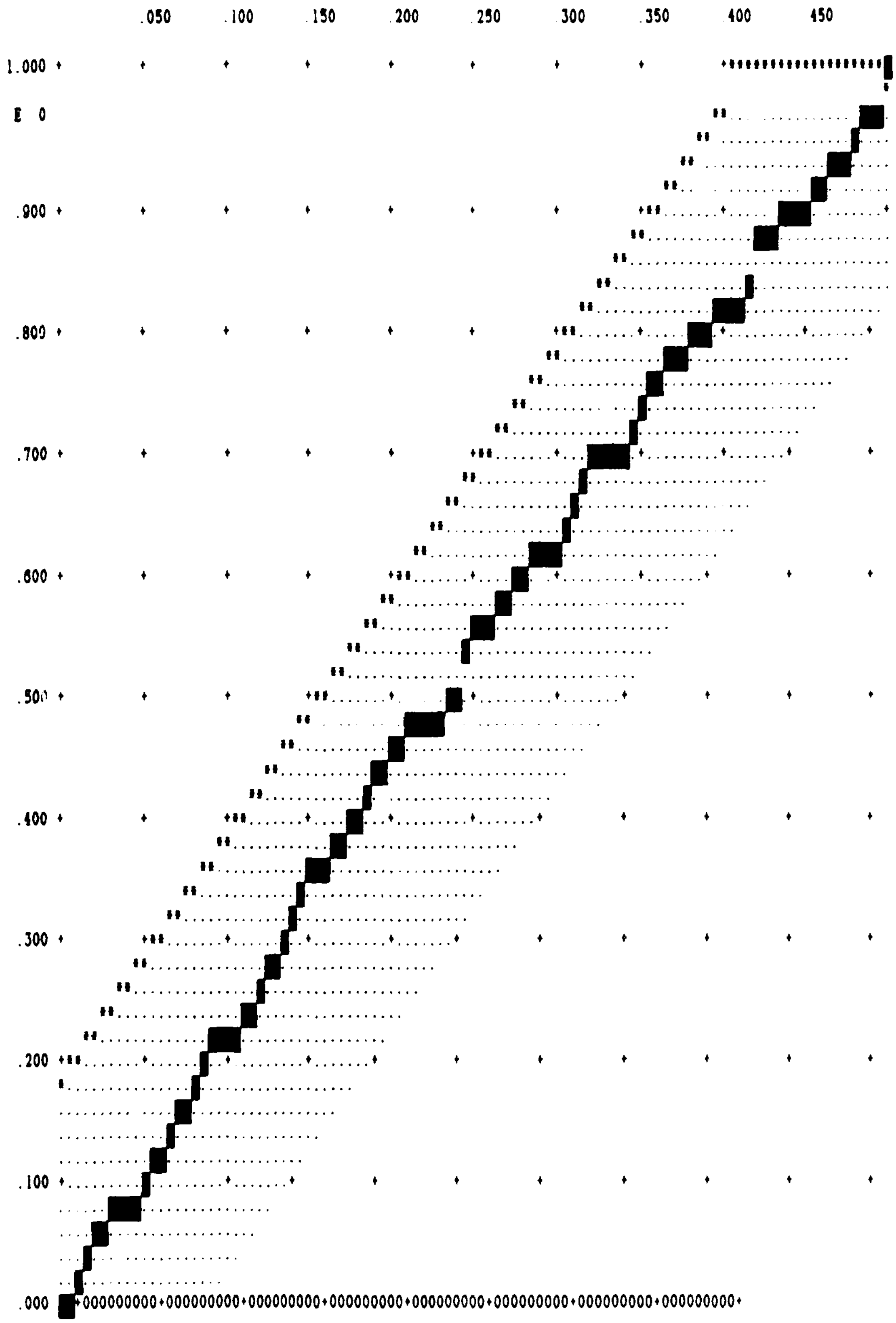

Figure B5. ASSY31 Transfer Function Cumulative Periodogram

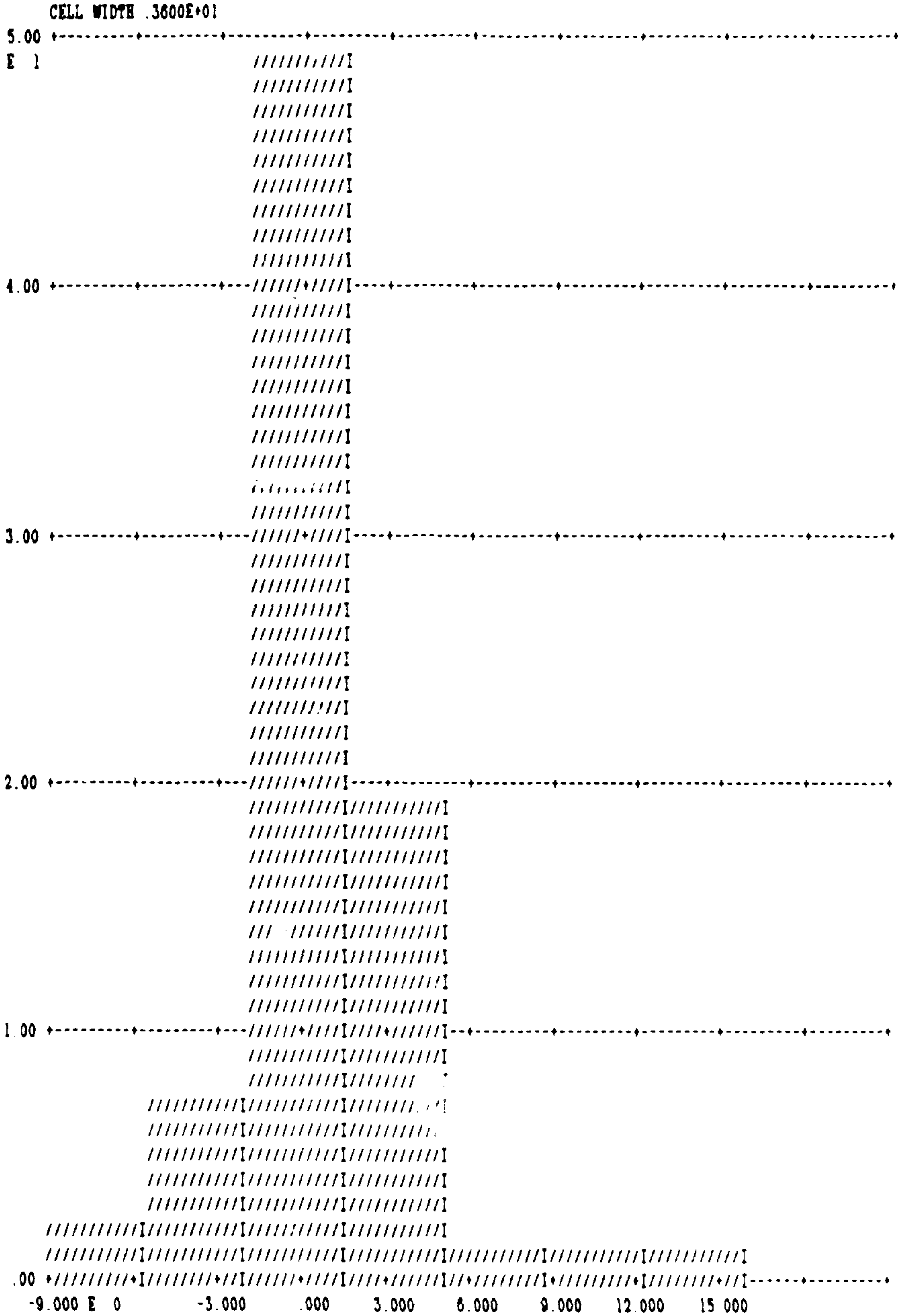

Figure B6. ASSY31 Transfer Function Histogram of Residuals

DATA - X = c135 flying hours 1978-1985 96 OBSERVATIONS
Y = demand data frame53

DIFFERENCING ON Y - 1 OF ORDER 1

DIFFERENCING ON X - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	MOVING AVERAGE 1	2	.19840E-01	-.19129E+00	.23097E+00

TRANSFER FUNCTION PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
2	INPUT LAG 1	0	-.24929E+00	-.22307E+01	.17322E+01

OPTIMUM VALUE OF B IS 0

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES .76899E+02 93 D.F. RESIDUAL MEAN SQUARE .82687E+00

NUMBER OF RESIDUALS 95 RESIDUAL STANDARD ERROR .90932E+00

Figure B7. FRAME53 Transfer Function Parameter Values

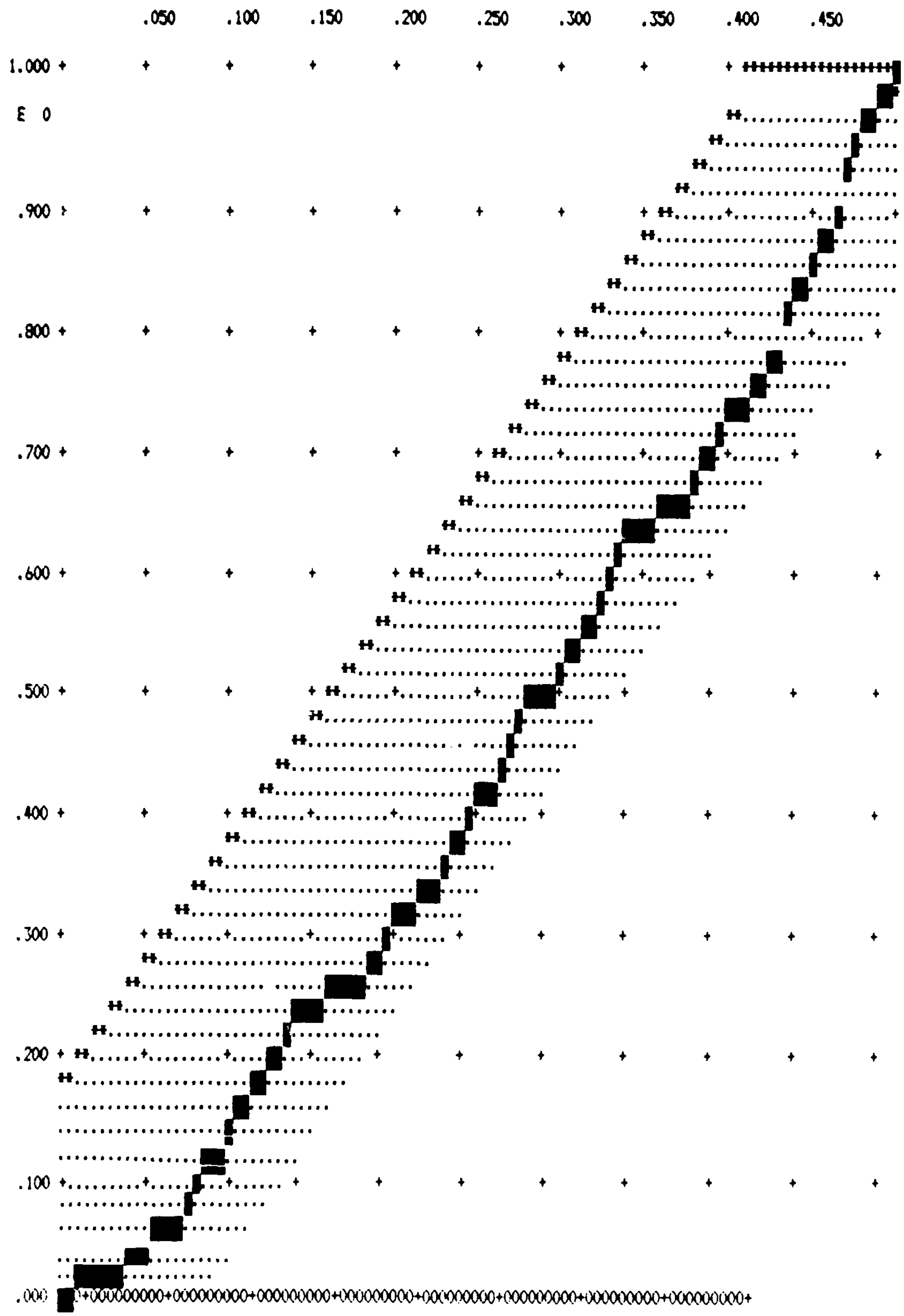

Figure B8. FRAME53 Transfer Function Cumulative Periodogram

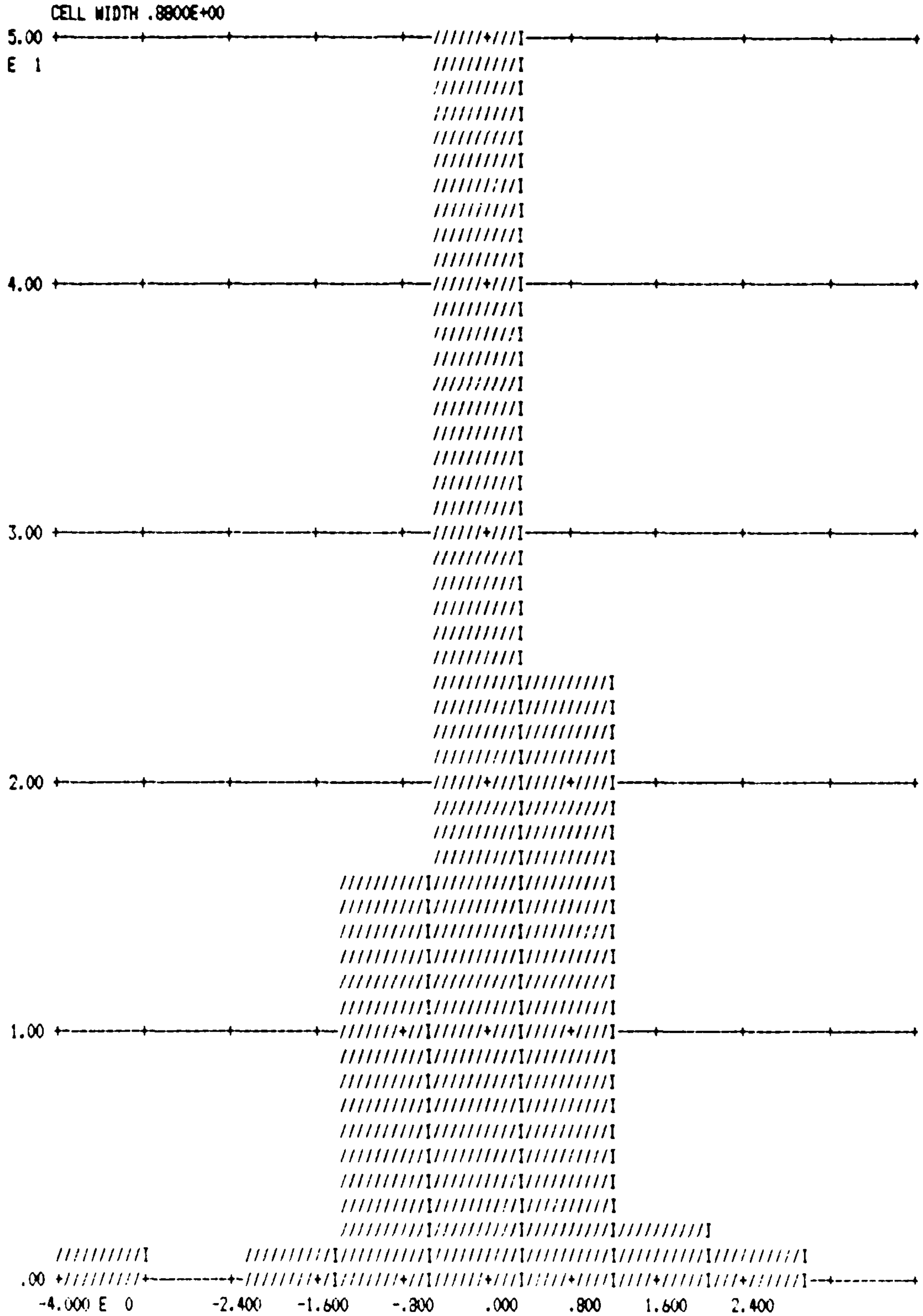

Figure B9. FRAME53 Transfer Function Histogram of Residuals

DATA - X = c135 flying hours 1978-1985 96 OBSERVATIONS
Y = demand data tail84

DIFFERENCING ON Y - 1 OF ORDER 1

DIFFERENCING ON X - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	MOVING AVERAGE 1	4	-.18260E-02	-.21161E+00	.20796E+00

TRANSFER FUNCTION PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
2	INPUT LAG 1	0	-.20435E+01	-.51458E+01	.10587E+01

OPTIMUM VALUE OF B IS 1

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.18842E+03	92 D.F.	RESIDUAL MEAN SQUARE	.20480E+01
NUMBER OF RESIDUALS	94		RESIDUAL STANDARD ERROR	.14311E+01

Figure B10. TAIL84 Transfer Function Parameter Values

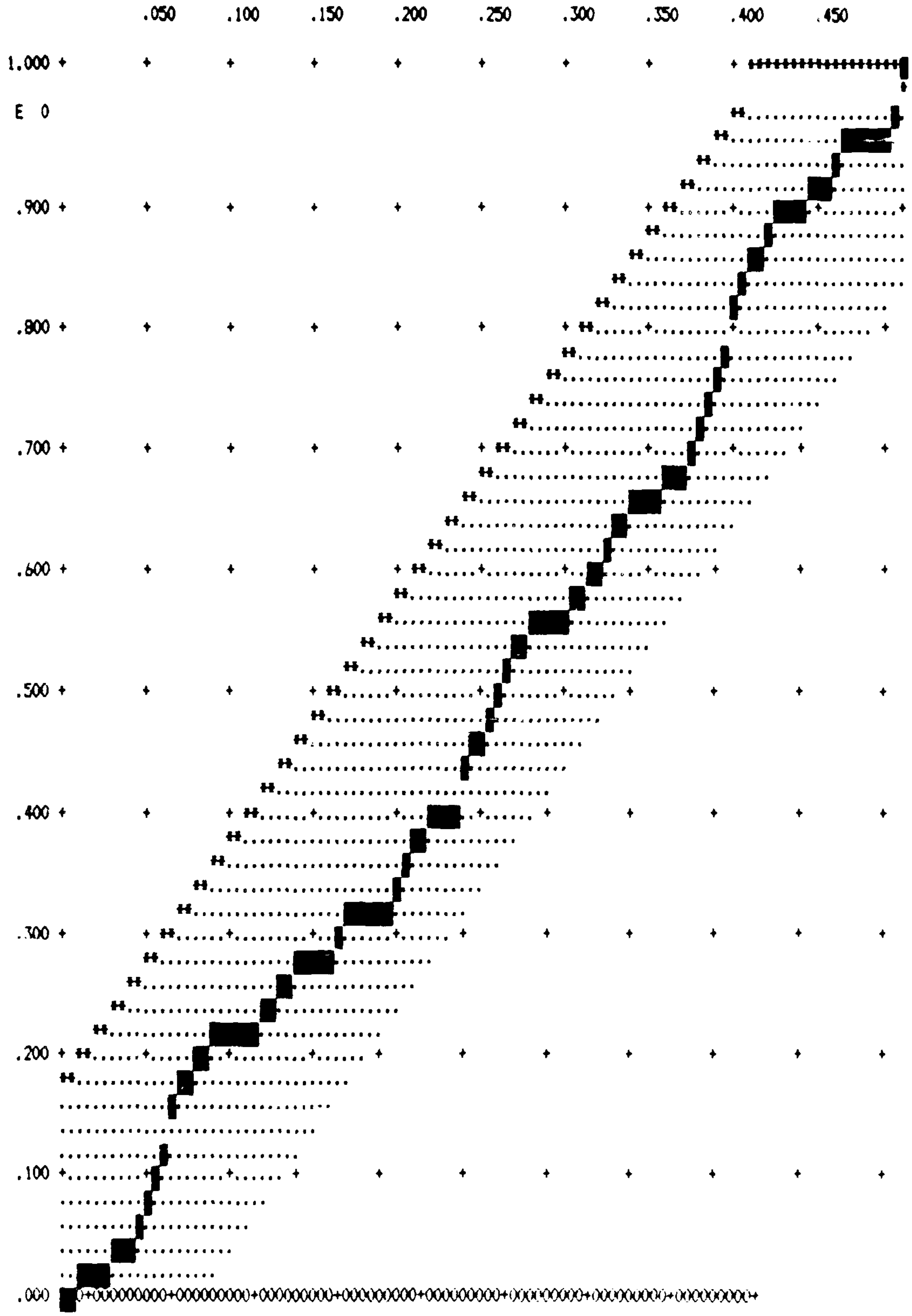

Figure B11. TAIL84 Transfer Function Cumulative Periodogram

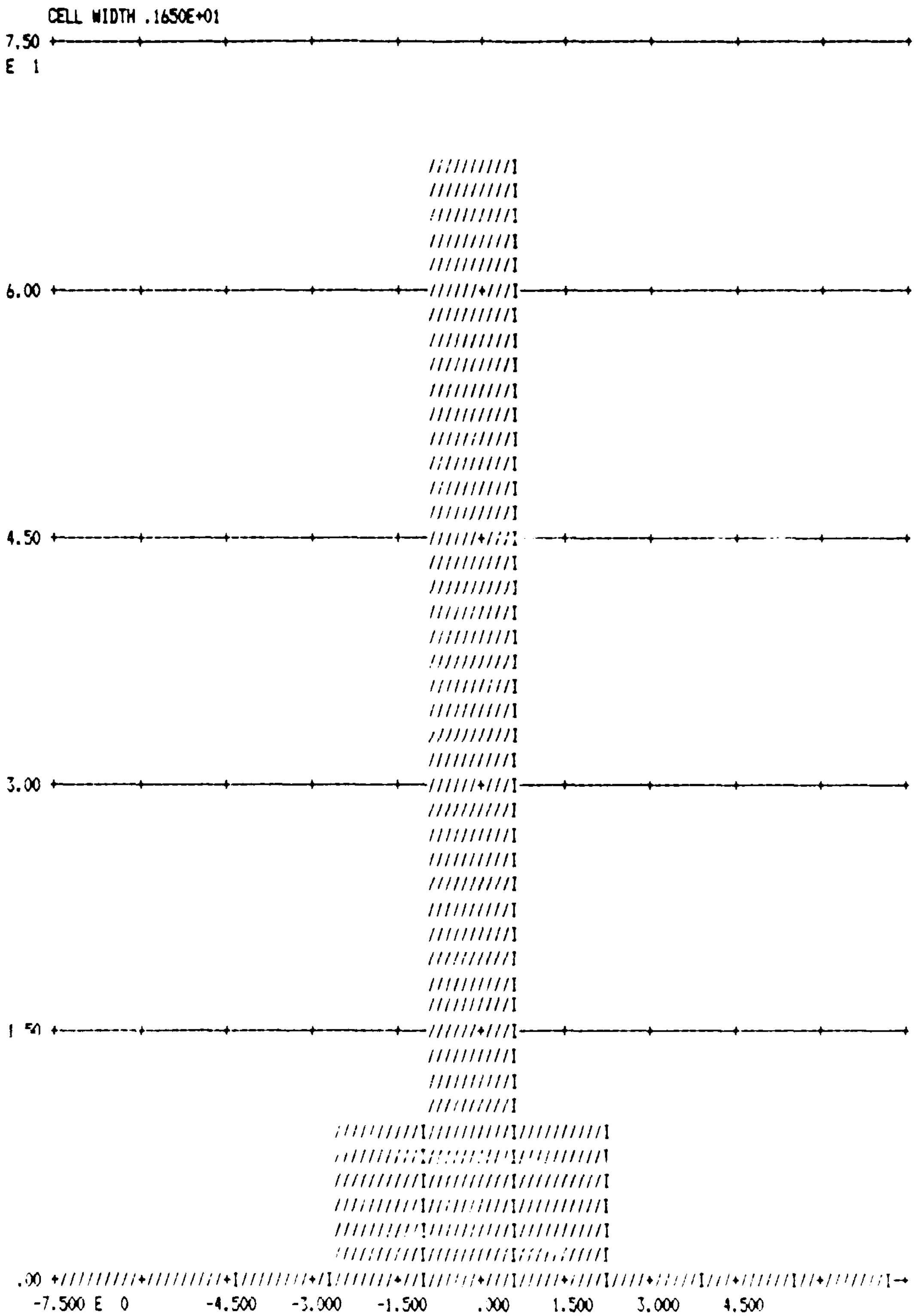

Figure B12. TAIL84 Transfer Function Histogram of Residuals

D... - X = c135 flying hours 1978-1985 96 OBSERVATIONS
Y = demand data cowl83

DIFFERENCING ON Y - 1 OF ORDER 1

DIFFERENCING ON X - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.12721E+00	-.34056E+00	.86134E-01
2	AUTOREGRESSIVE 1	2	-.12823E+00	-.34246E+00	.85992E-01
3	MOVING AVERAGE 1	3	-.17424E+00	-.38912E+00	.40644E-01

TRANSFER FUNCTION PARAMETERS

4	INPUT LAG 1	0	-.27233E+00	-.23134E+01	.17687E+01

OPTIMUM VALUE OF B IS 0

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.72103E+02	89 D.F.	RESIDUAL MEAN SQUARE	.81015E+00
NUMBER OF RESIDUALS	93		RESIDUAL STANDARD ERROR	.90008E+00

Figure B13. COWL83 Transfer Function Parameter Values

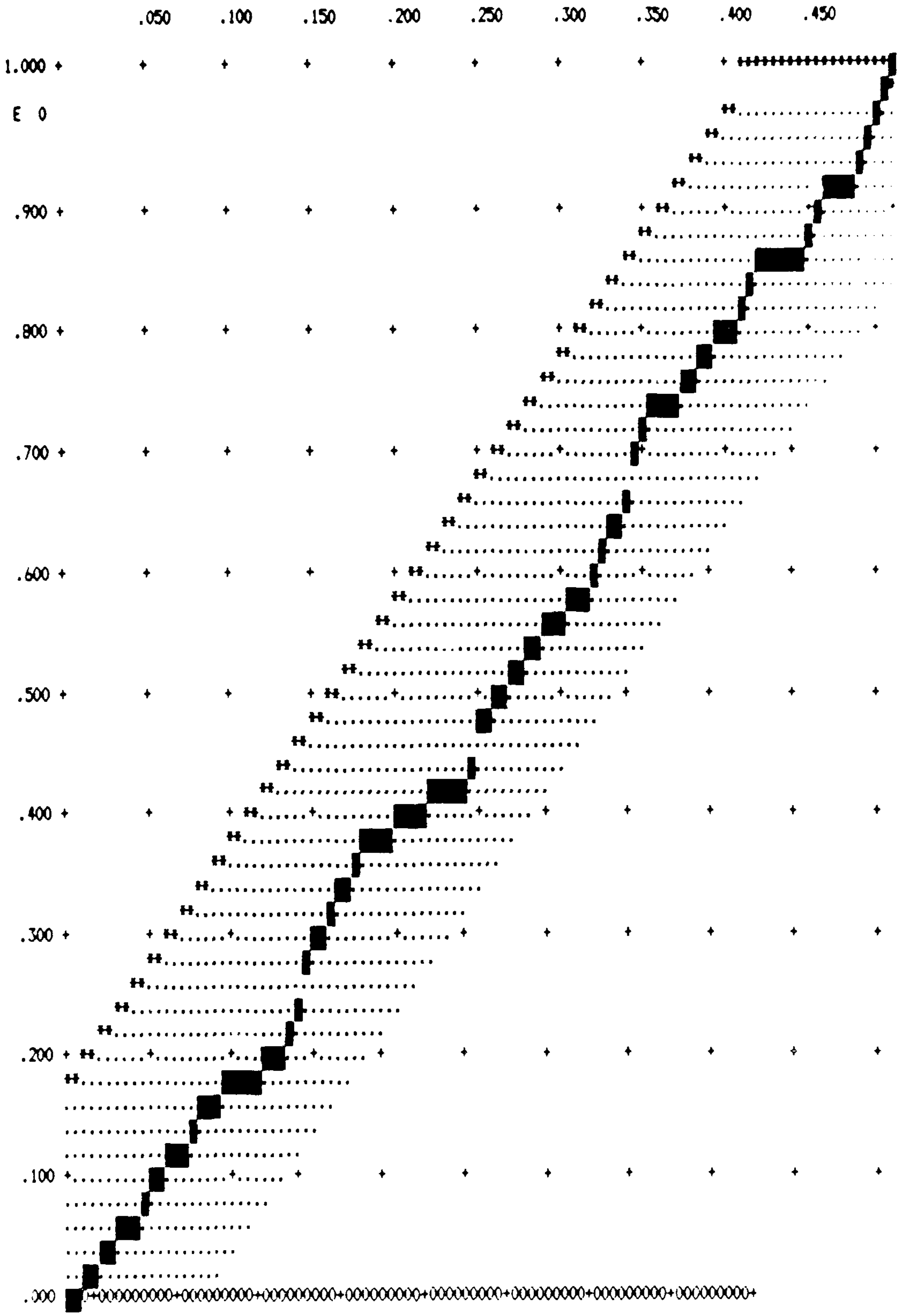

Figure B14. COWL83 Transfer Function Cumulative Periodogram

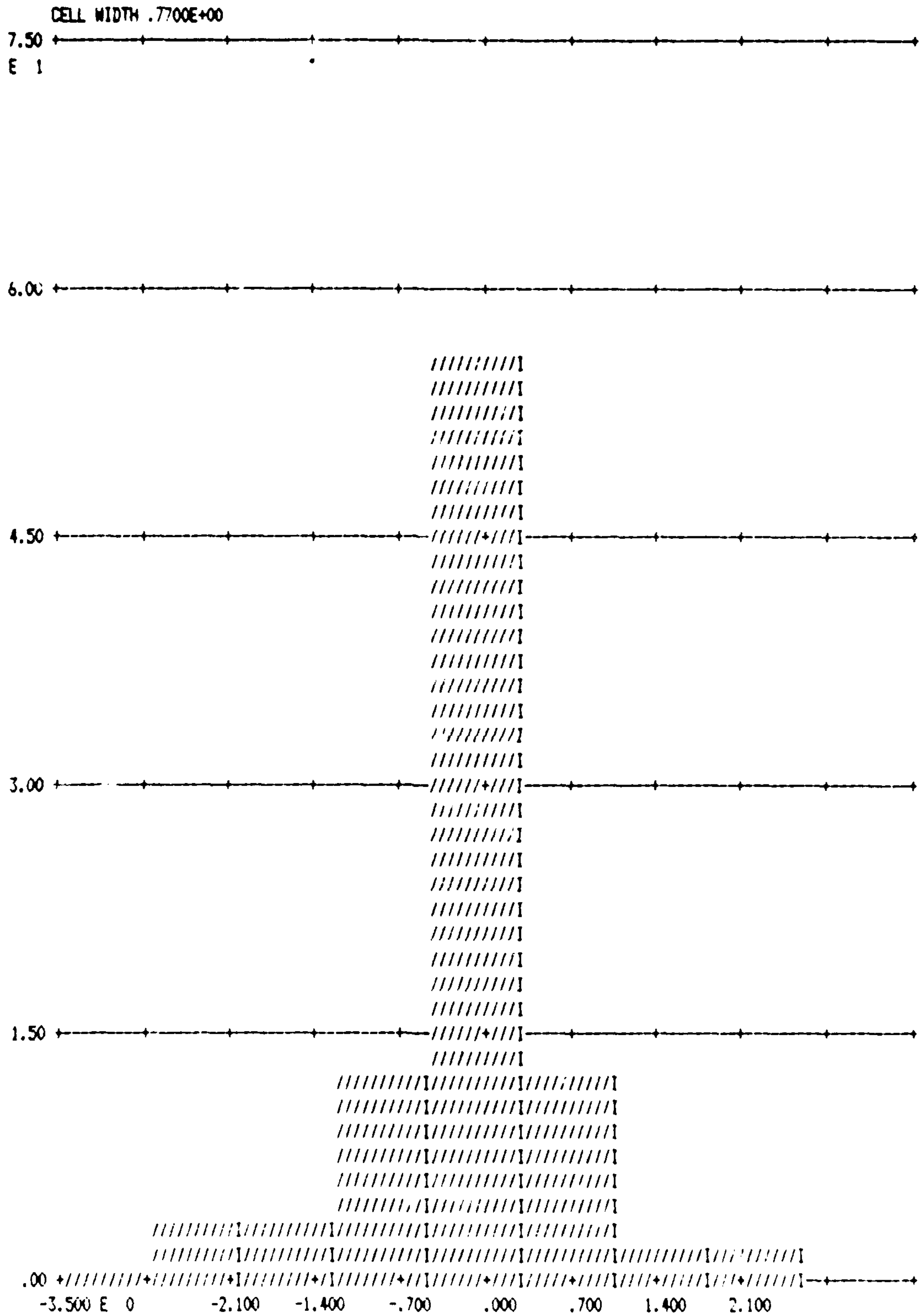

Figure B15. COWL83 Transfer Function Histogram of Residuals

DATA - X = c135 flying hours 1978-1985 96 OBSERVATIONS
Y = demand data slve85

DIFFERENCING ON Y - 1 OF ORDER 1

DIFFERENCING ON X - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.62894E-01	-.27714E+00	.15136E+00
2	MOVING AVERAGE 1	2	.57363E-01	-.15564E+00	.27037E+00
3	MOVING AVERAGE 1	3	-.30270E+00	-.51171E+00	-.93686E-01

TRANSFER FUNCTION PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
4	INPUT LAG 1	0	.13212E+00	-.25233E+01	.27876E+01
5	INPUT LAG 1	1	-.66062E+00	-.33054E+01	.19842E+01

OPTIMUM VALUE OF B IS 0

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.11866E+03	88 D.F.	RESIDUAL MEAN SQUARE	.13484E+01
NUMBER OF RESIDUALS	93		RESIDUAL STANDARD ERROR	.11612E+01

Figure B16. SLVE85 Transfer Function Parameter Values

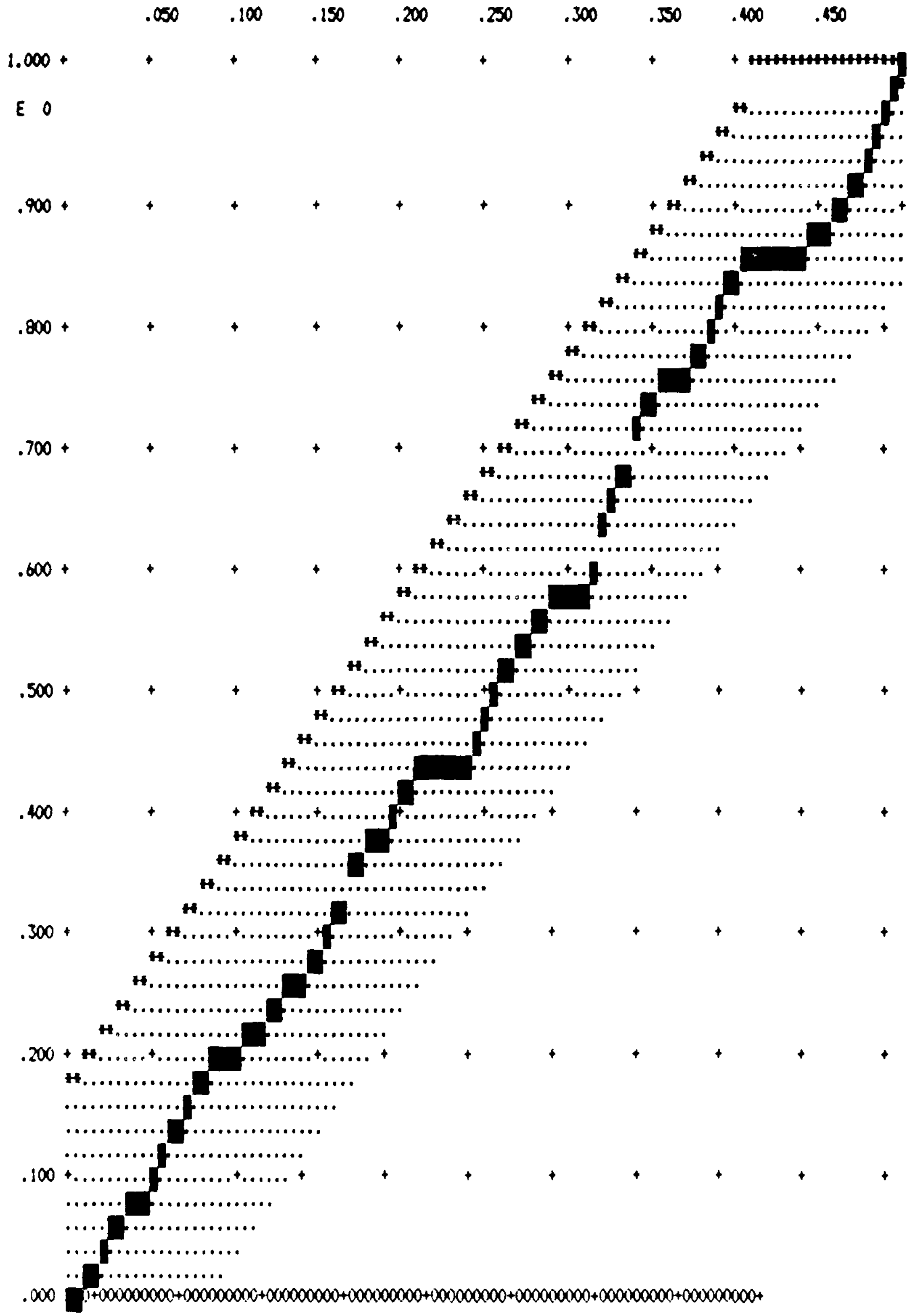

Figure B17. SLVE85 Transfer Function Cumulative Periodogram

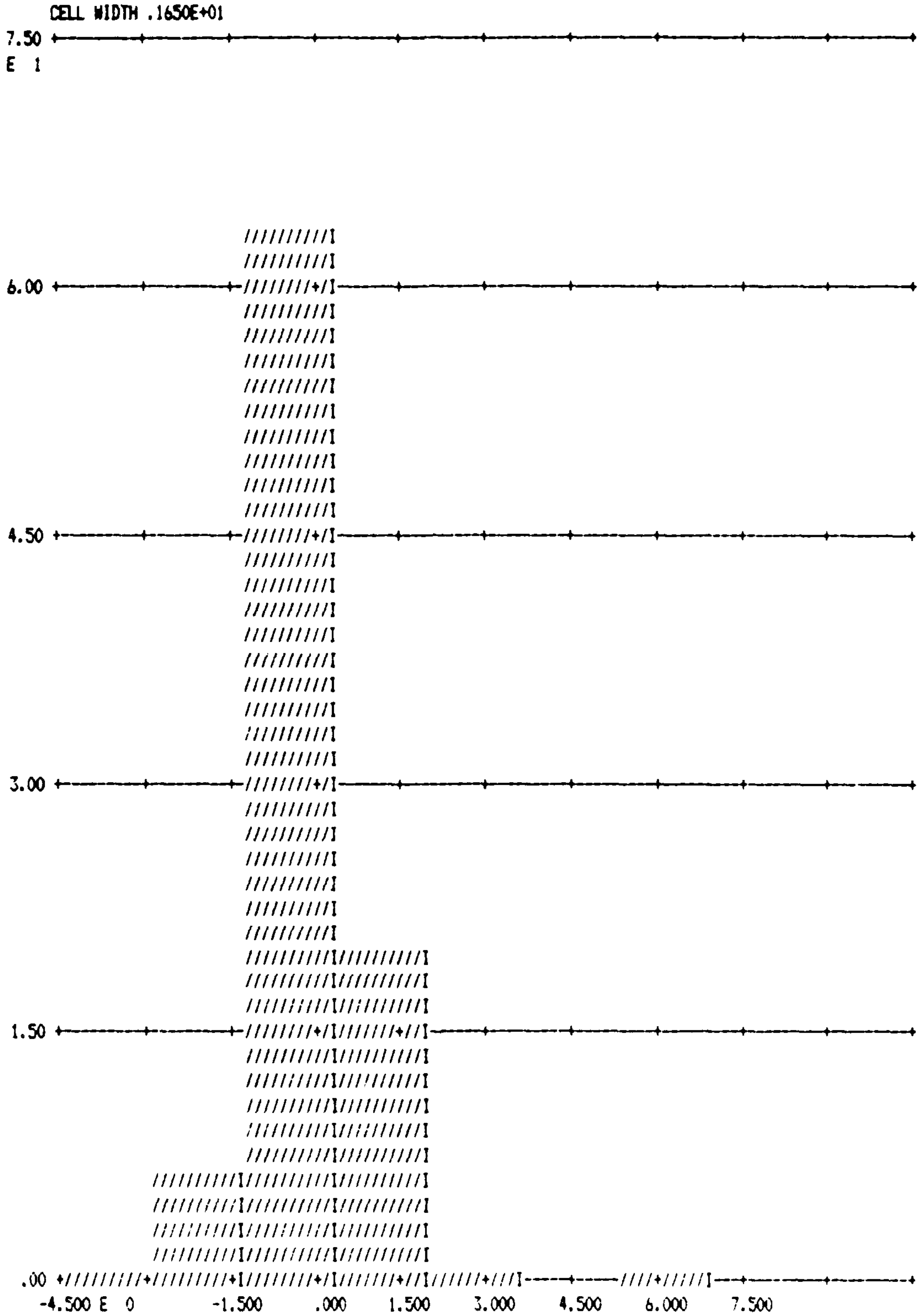

Figure B18. SLVE85 Transfer Function Histogram of Residuals

```
DATA - X = c135 flying hours 1978-1985                                                          96 OBSERVATIONS
       Y = demand data assy32

DIFFERENCING ON Y - 1 OF ORDER  1

DIFFERENCING ON X - 1 OF ORDER  1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

################################################################################################

NOISE MODEL PARAMETERS

################################################################################################

PARAMETER        PARAMETER          PARAMETER     ESTIMATED                 95 PER CENT
 NUMBER             TYPE              ORDER         VALUE         LOWER LIMIT         UPPER LIMIT

################################################################################################

   1         MOVING AVERAGE 1          3        -.37648E+00      -.57047E+00        -.18249E+00

################################################################################################

TRANSFER FUNCTION PARAMETERS

################################################################################################

   2          INPUT LAG 1              0         .63294E+01      -.15040E+01         .14163E+02

################################################################################################

OPTIMUM VALUE OF B IS  0

################################################################################################

OTHER INFORMATION AND RESULTS

################################################################################################

RESIDUAL SUM OF SQUARES      .14136E+04    93 D.F.           RESIDUAL MEAN SQUARE          .15200E+02

NUMBER OF RESIDUALS                  95                      RESIDUAL STANDARD ERROR       .38988E+01
```

Figure B19. ASSY32 Transfer Function Parameter Values

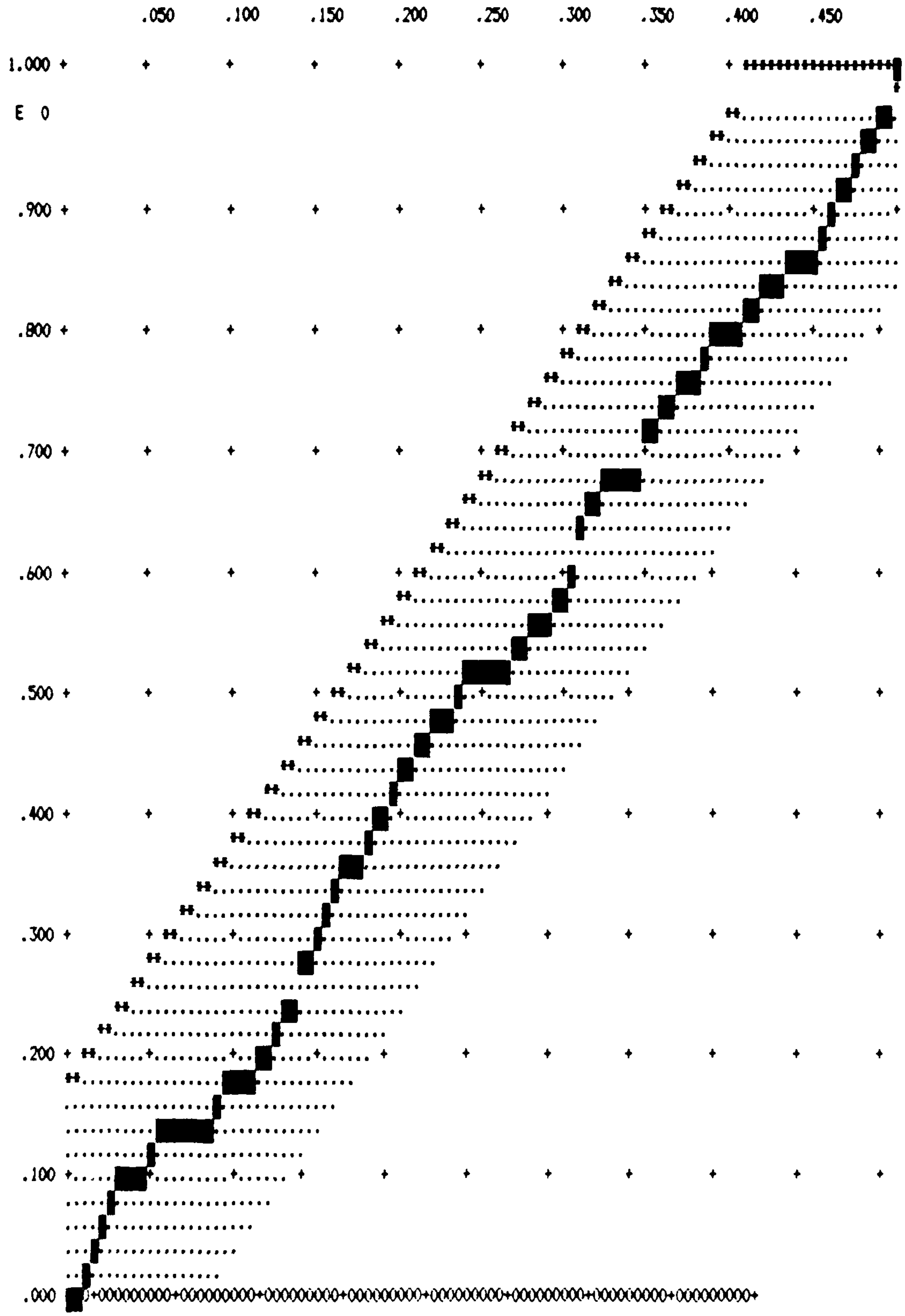

Figure B20. ASSY32 Transfer Function Cumulative Periodogram

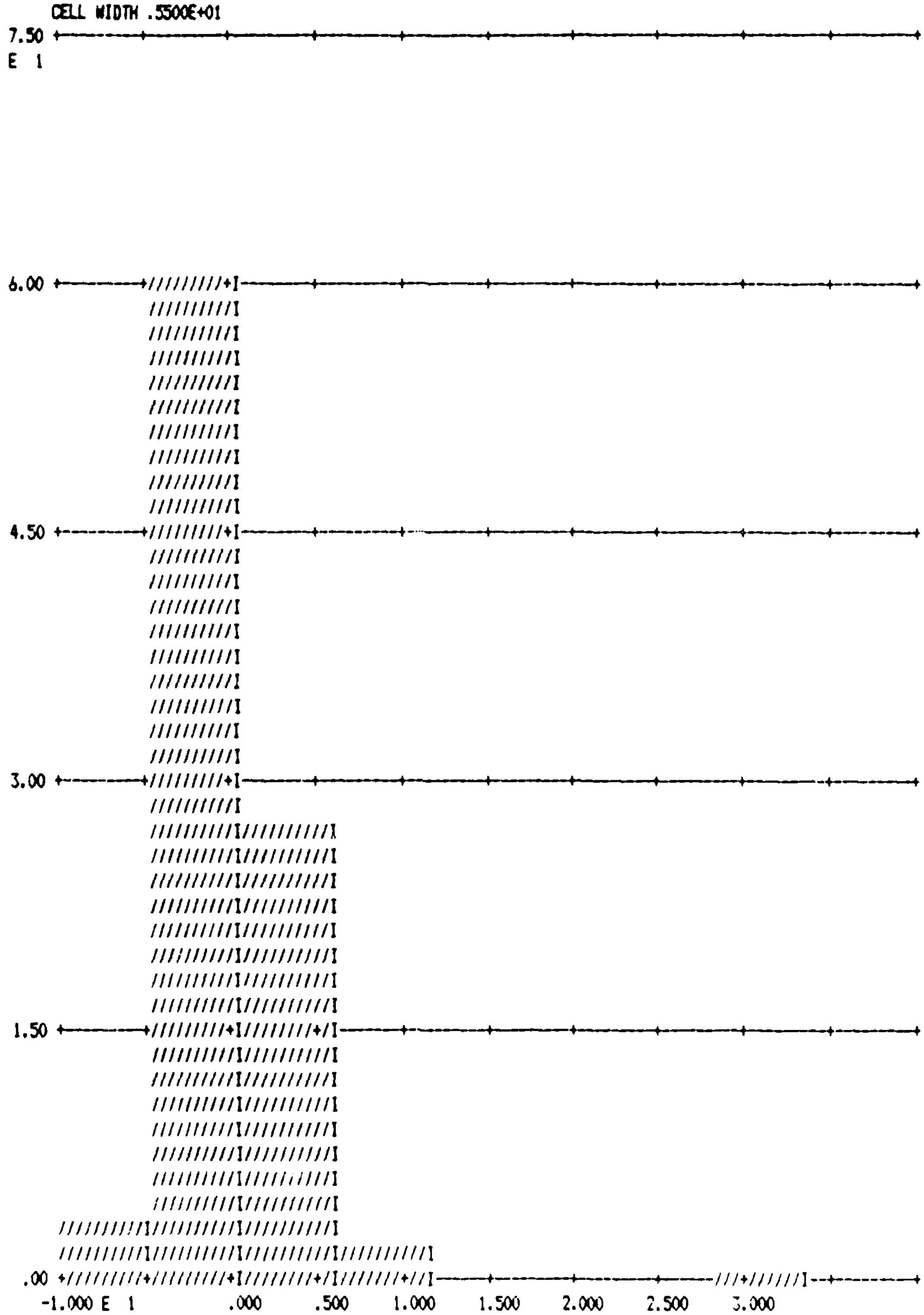

Figure B21. ASSY32 Transfer Function Histogram of Residuals

```
DATA - X = c135 flying hours 1978-1985                                     96 OBSERVATIONS
       Y = demand data assy33

DIFFERENCING ON Y - 1 OF ORDER  1

DIFFERENCING ON X - 1 OF ORDER  1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

###########################################################################################

NOISE MODEL PARAMETERS

###########################################################################################

PARAMETER        PARAMETER        PARAMETER    ESTIMATED           95 PER CENT
 NUMBER            TYPE             ORDER        VALUE       LOWER LIMIT      UPPER LIMIT

###########################################################################################

###########################################################################################

TRANSFER FUNCTION PARAMETERS

###########################################################################################

    1           INPUT LAG 1            0       .12178E+01    -.57504E+01      .81861E+01

###########################################################################################

OPTIMUM VALUE OF B IS  0

###########################################################################################

OTHER INFORMATION AND RESULTS

###########################################################################################

RESIDUAL SUM OF SQUARES     .98672E+03   94 D.F.       RESIDUAL MEAN SQUARE         .10497E+02

NUMBER OF RESIDUALS                 95                 RESIDUAL STANDARD ERROR      .32399E+01
```

Figure B22. ASSY33 Transfer Function Parameter Values

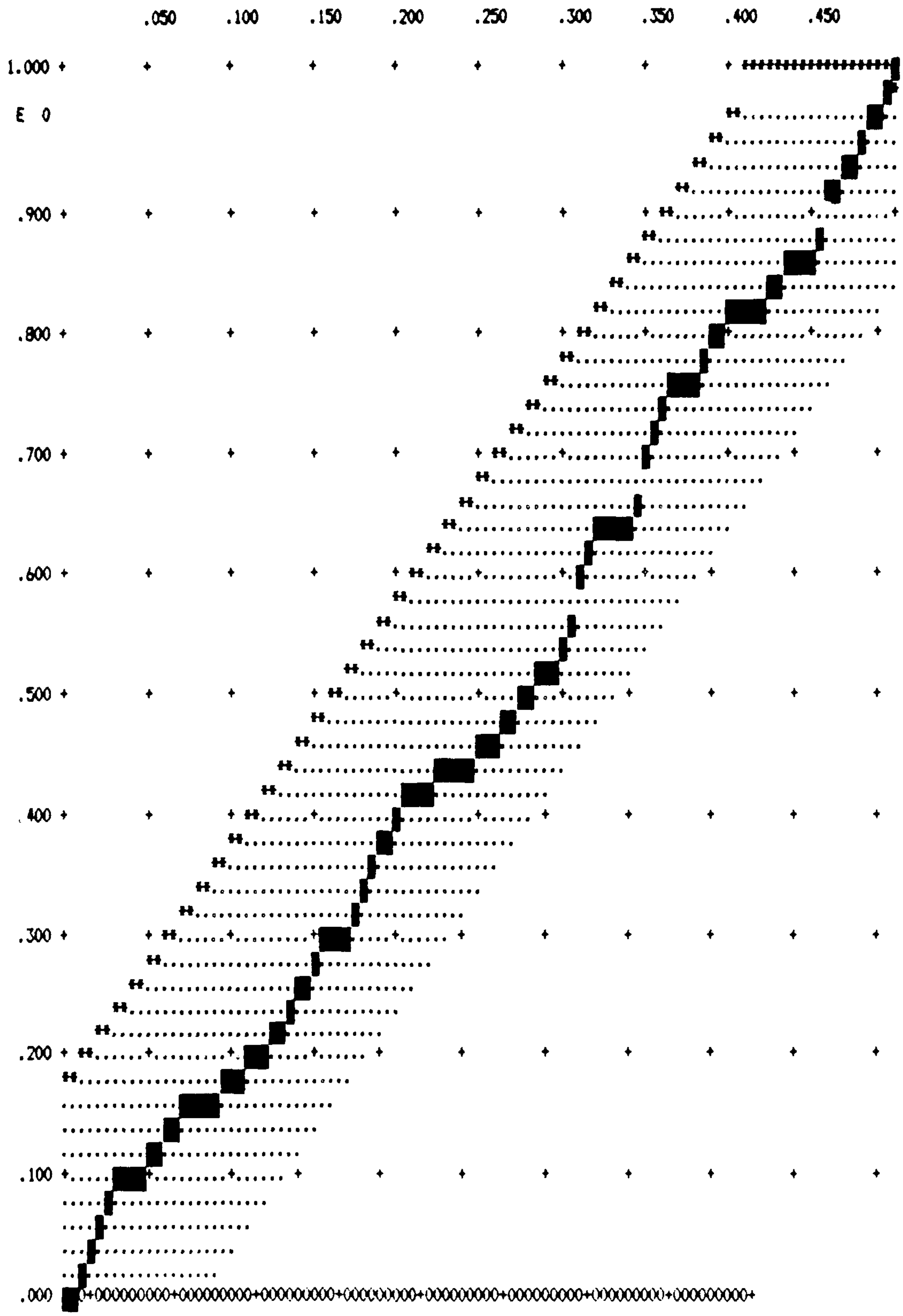

Figure B23. ASSY33 Transfer Function Cumulative Periodogram

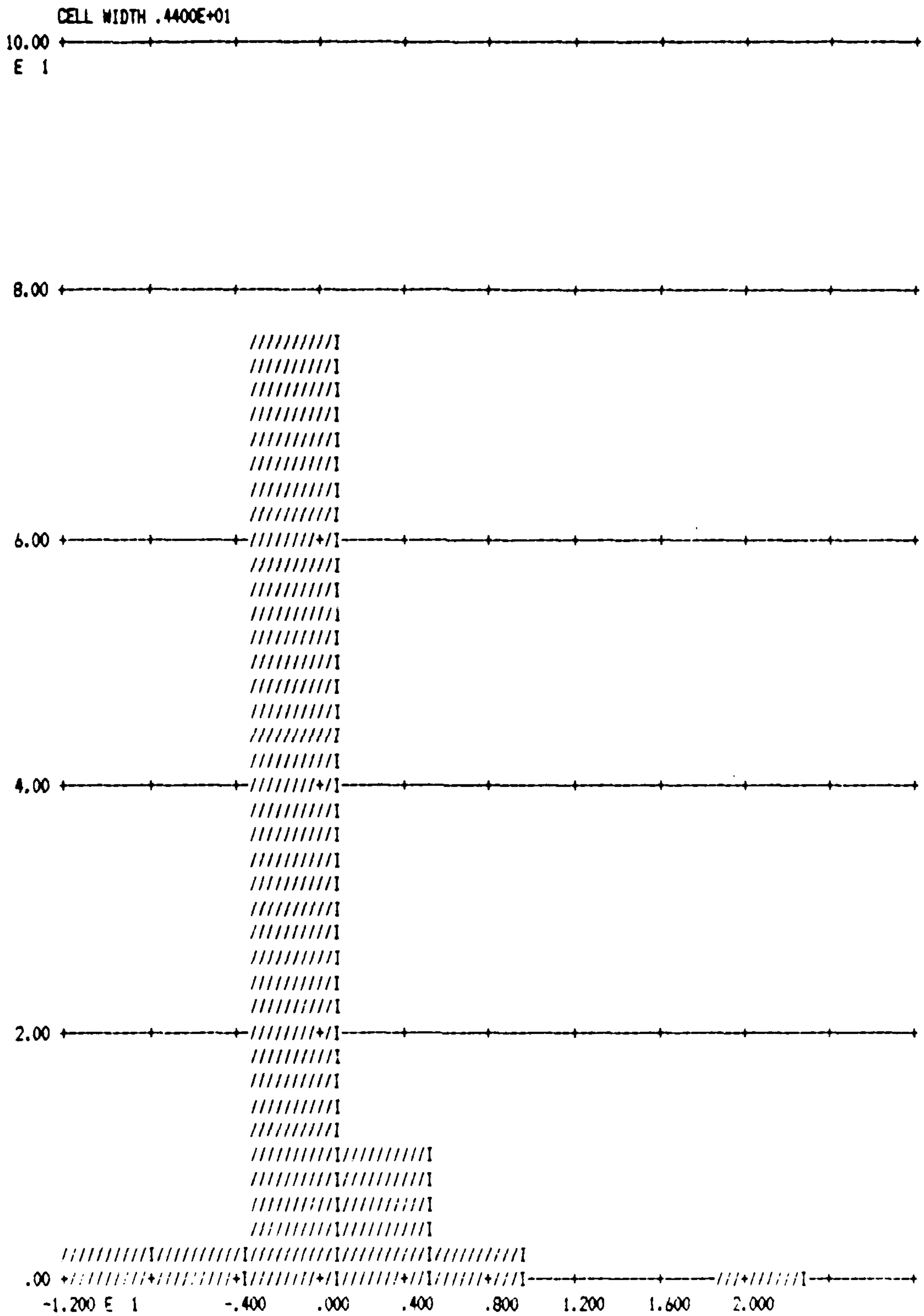

Figure B24. ASSY33 Transfer Function Histogram of Residuals

DATA - X = c135 flying hours 1978-1985 | 96 OBSERVATIONS
Y = demand data fork35

DIFFERENCING ON Y - 1 OF ORDER 1

DIFFERENCING ON X - 1 OF ORDER 1

MODEL DEVELOPED WITH TRANSFORMED DATA = LOG(X(T)+ .00000E+00)

NOISE MODEL PARAMETERS

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	6	.32033E+00	.48745E-01	.59192E+00
2	MOVING AVERAGE 1	1	.16500E+00	-.59507E-01	.38950E+00

TRANSFER FUNCTION PARAMETERS

3	INPUT LAG 1	0	-.12686E+01	-.40913E+01	.15541E+01
4	INPUT LAG 1	1	.61395E+00	-.24714E+01	.36993E+01
5	INPUT LAG 1	2	.14256E+01	-.13788E+01	.42301E+01

OPTIMUM VALUE OF B IS 4

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.92377E+02	78 D.F.	RESIDUAL MEAN SQUARE	.11843E+01
NUMBER OF RESIDUALS	83		RESIDUAL STANDARD ERROR	.10883E+01

Figure B25. FORK35 Transfer Function Parameter Values

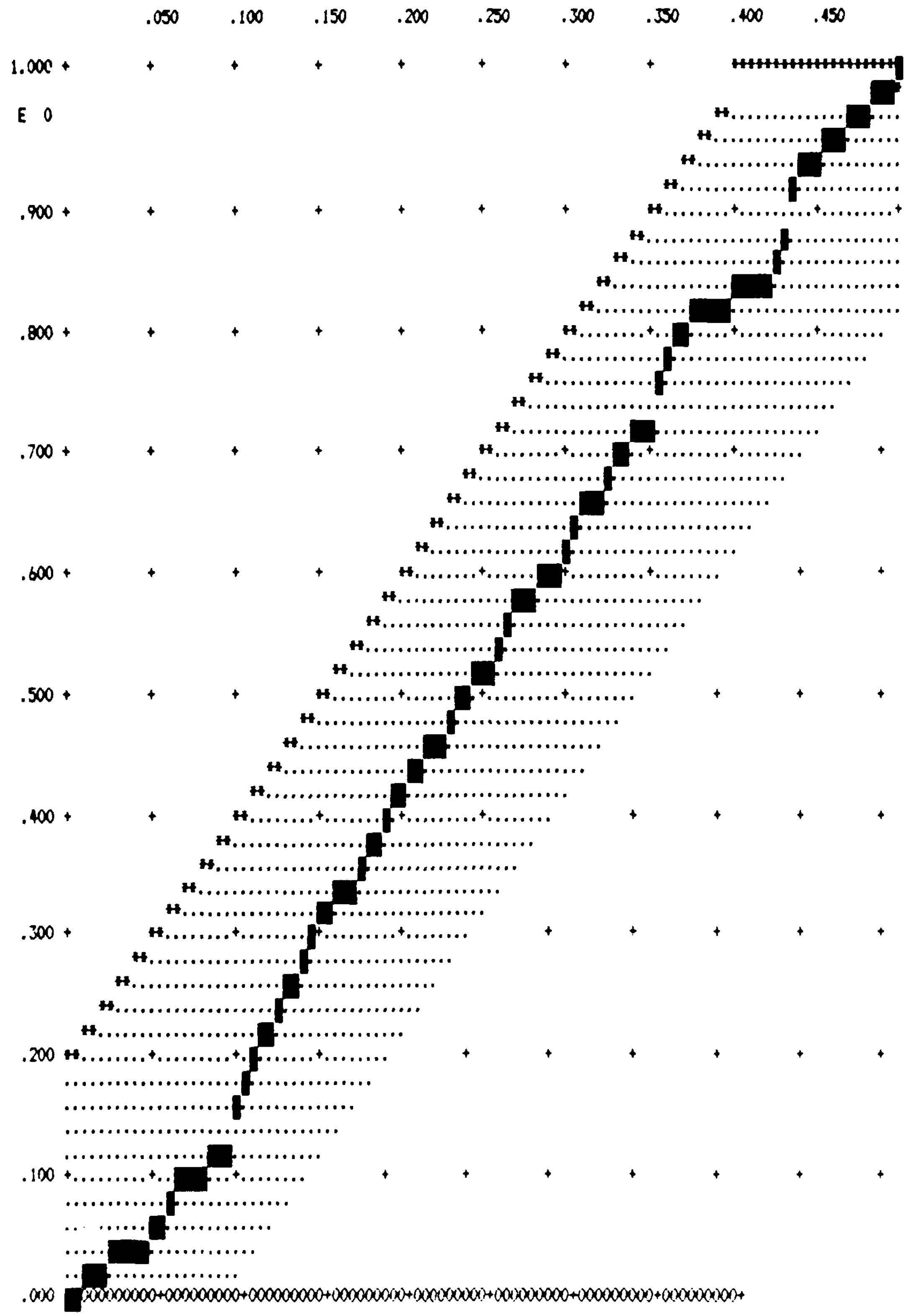

Figure B26. FORK35 Transfer Function Cumulative Periodogram

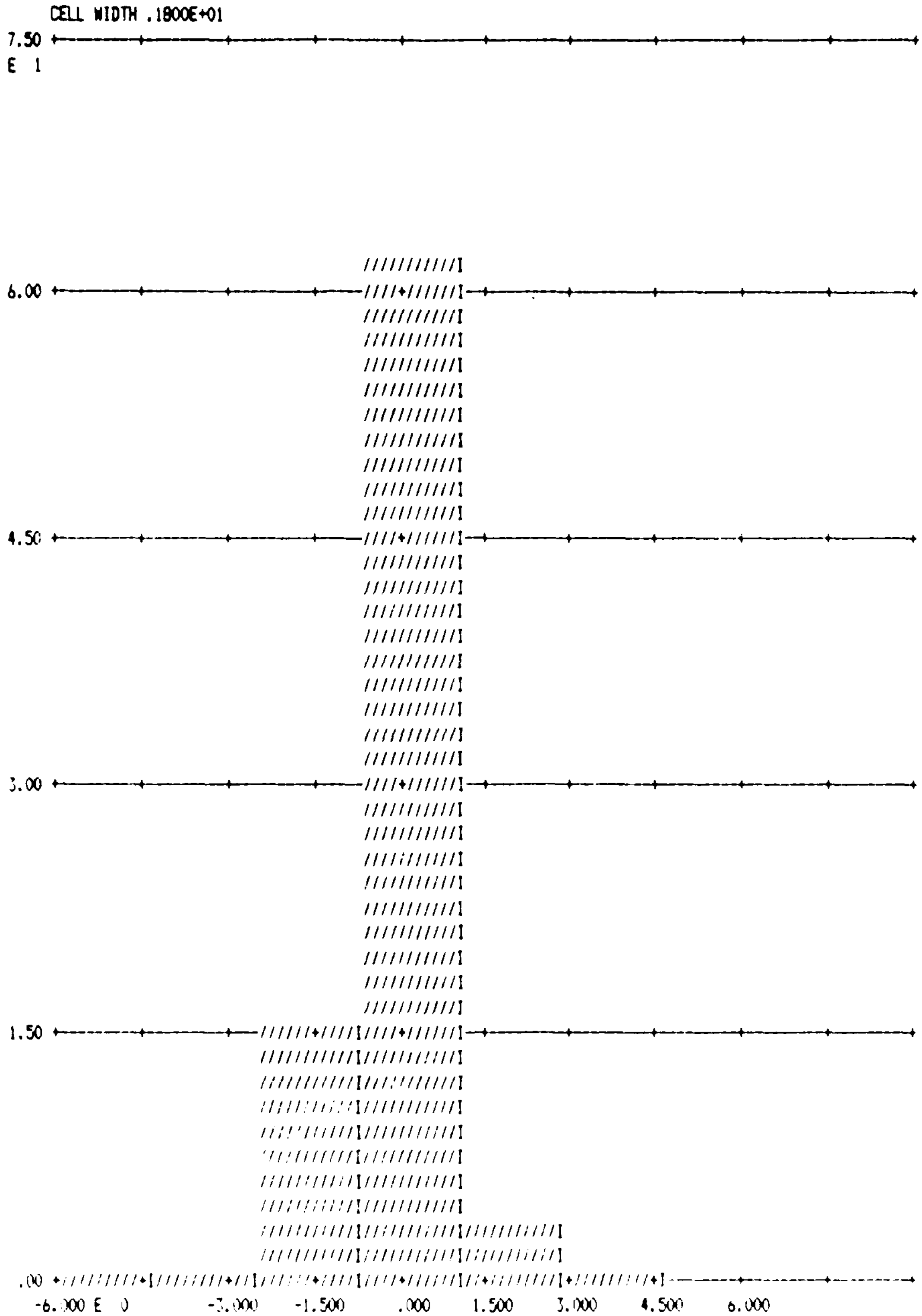

Figure B27. FORK35 Transfer Function Histogram of Residuals

Appendix C: Univariate Models

SUMMARY OF MODEL 1

##

DATA - Z = demand data　　　96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

##

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.10630E+00	-.31513E+00	.10252E+00
2	AUTOREGRESSIVE 1	3	-.13600E+00	-.34600E+00	74093E-01
3	MOVING AVERAGE 1	4	.89832E-01	-.89349E-01	26901E+00
4	MOVING AVERAGE 1	6	-.58958E+00	-.76853E+00	- 41064E+00

##

OTHER INFORMATION AND RESULTS

##

RESIDUAL SUM OF SQUARES	.20158E+03	88 D.F.	RESIDUAL MEAN SQUARE	.22906E+01
NUMBER OF RESIDUALS	92		RESIDUAL STANDARD ERROR	.15135E+01

Figure C1. FAIR01 Univariate Parameter Values

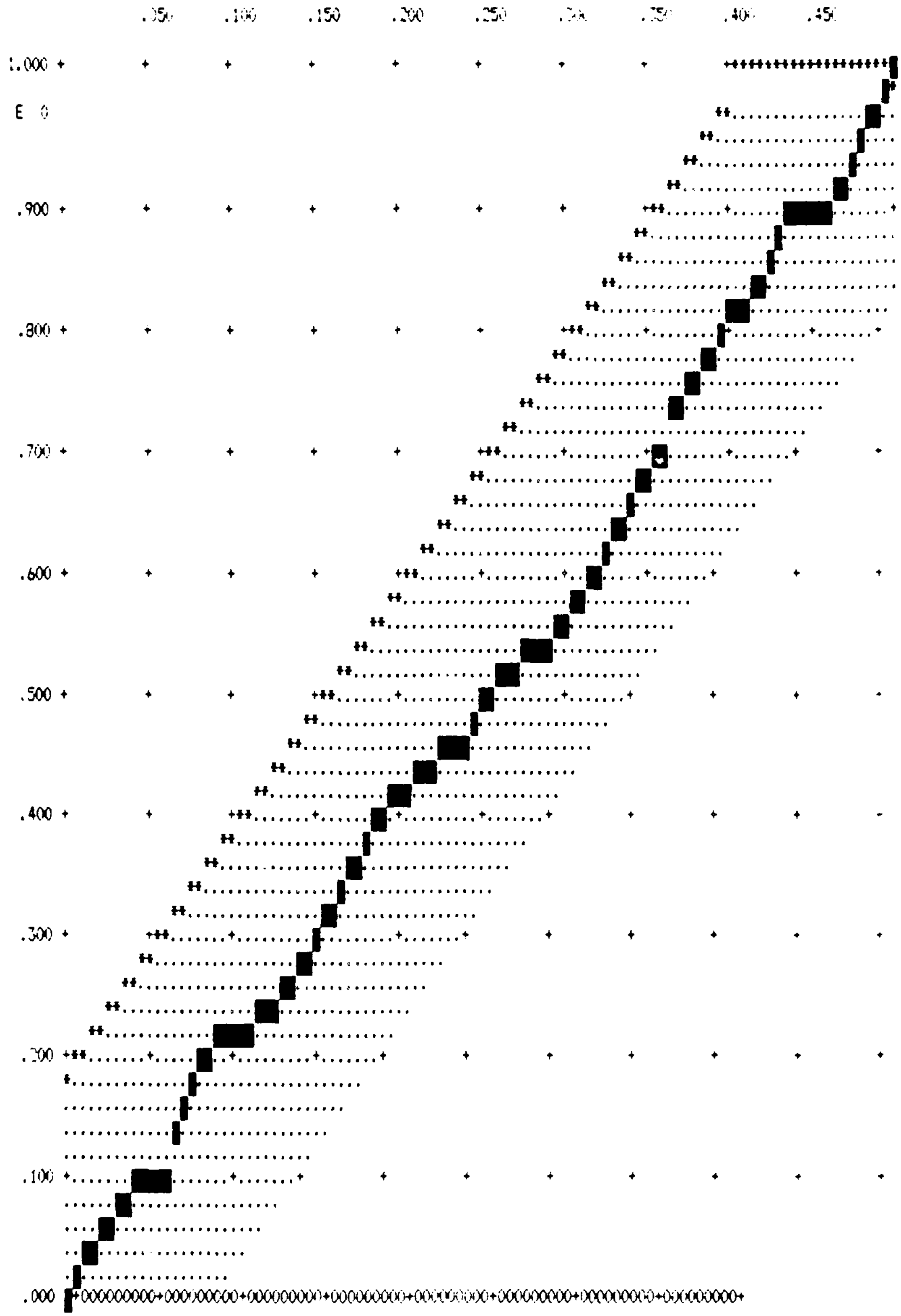

Figure C2. FAIR01 Univariate Cumulative Periodogram

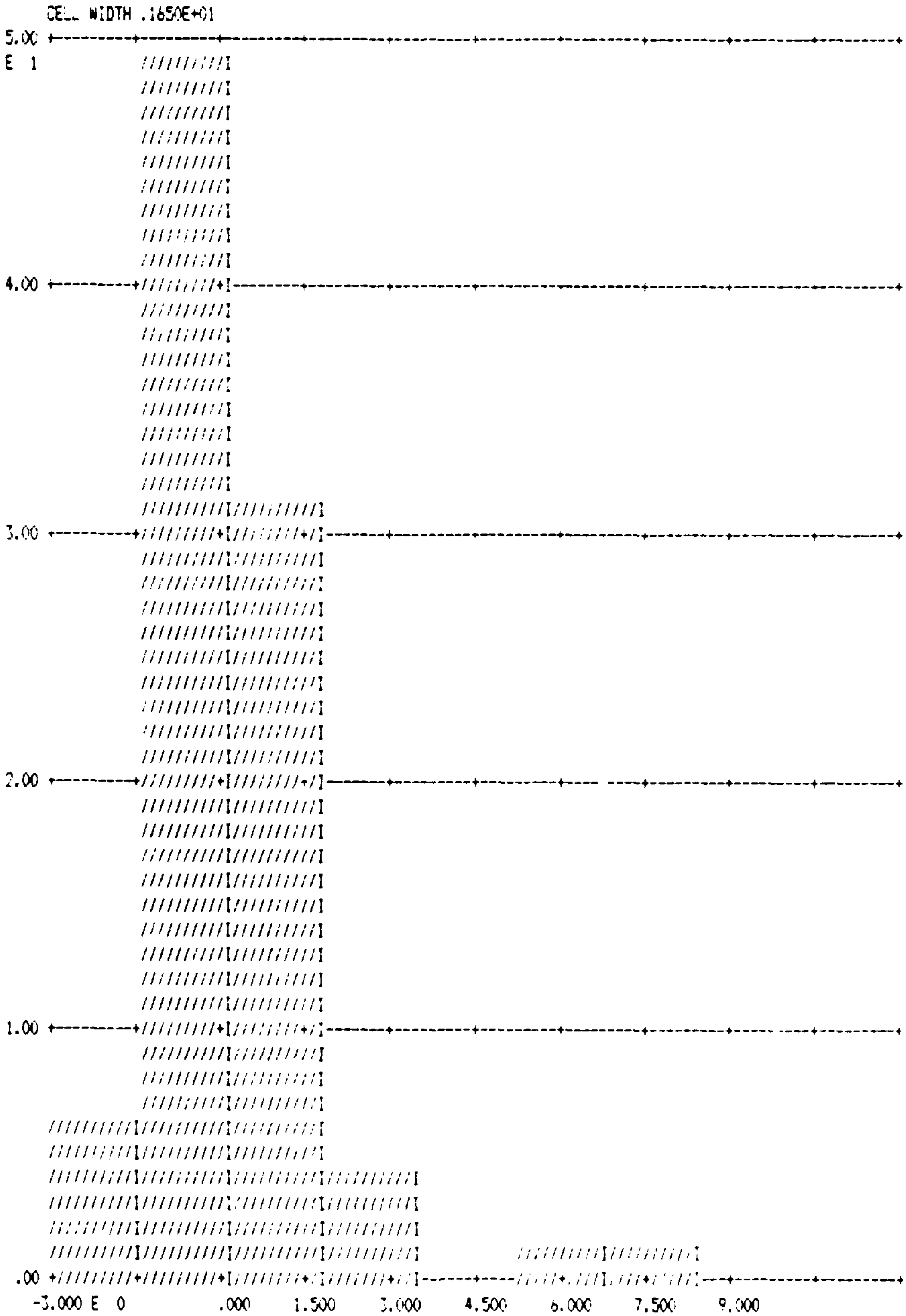

Figure C3. FAIR01 Univariate Histogram of Residuals

PREWHITENED demand data
LOG10 SPECTRUM SMOOTHING BANDWIDTH = .098 APPROX 95 P.C. CONFIDENCE LIMITS

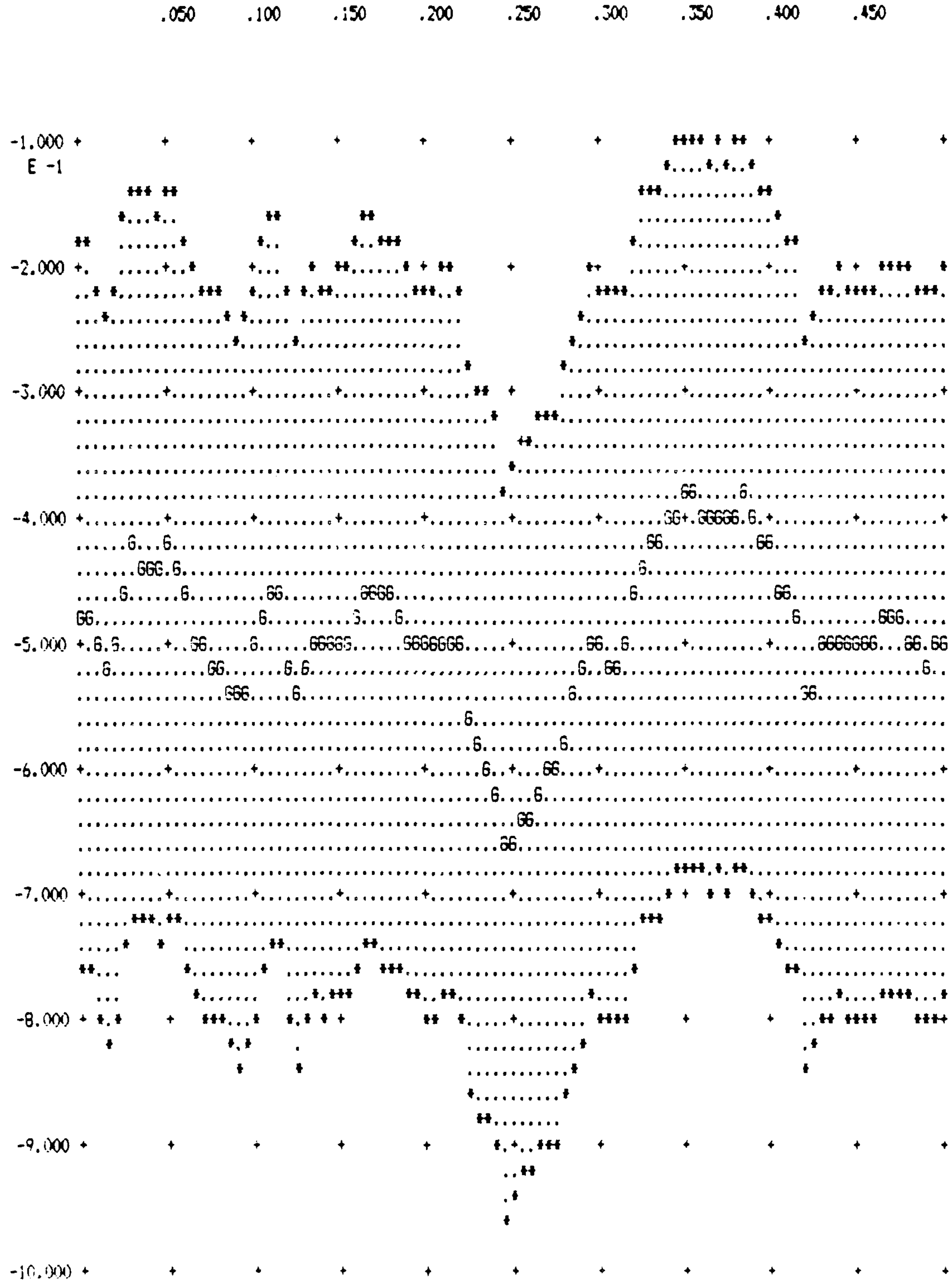

Figure C4. FAIR01 Univariate Power Spectrum

SUMMARY OF MODEL 1

##

DATA - Z = demand data assy31 96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

##

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	MOVING AVERAGE 1	3	-.19682E+00	-.39780E+00	.41662E-02
2	MOVING AVERAGE 1	6	-.32083E+00	-.52257E+00	-.11909E+00

##

OTHER INFORMATION AND RESULTS

##

RESIDUAL SUM OF SQUARES	.61632E+03	93 D.F.	RESIDUAL MEAN SQUARE	.66271E+01
NUMBER OF RESIDUALS	95		RESIDUAL STANDARD ERROR	.25743E+01

Figure C5. ASSY31 Univariate Parameter Values

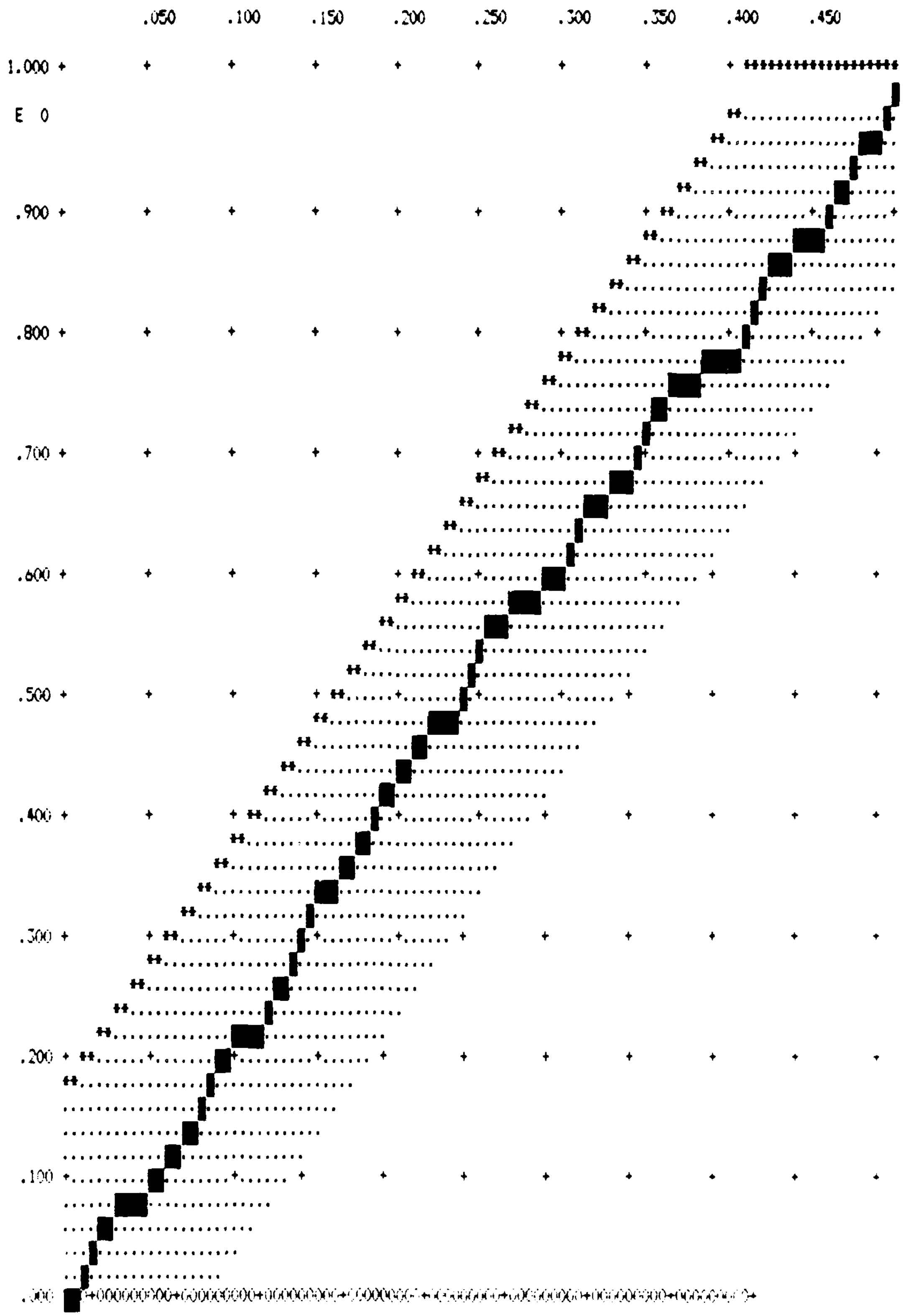

Figure C6. ASSY31 Univariate Cumulative Periodogram

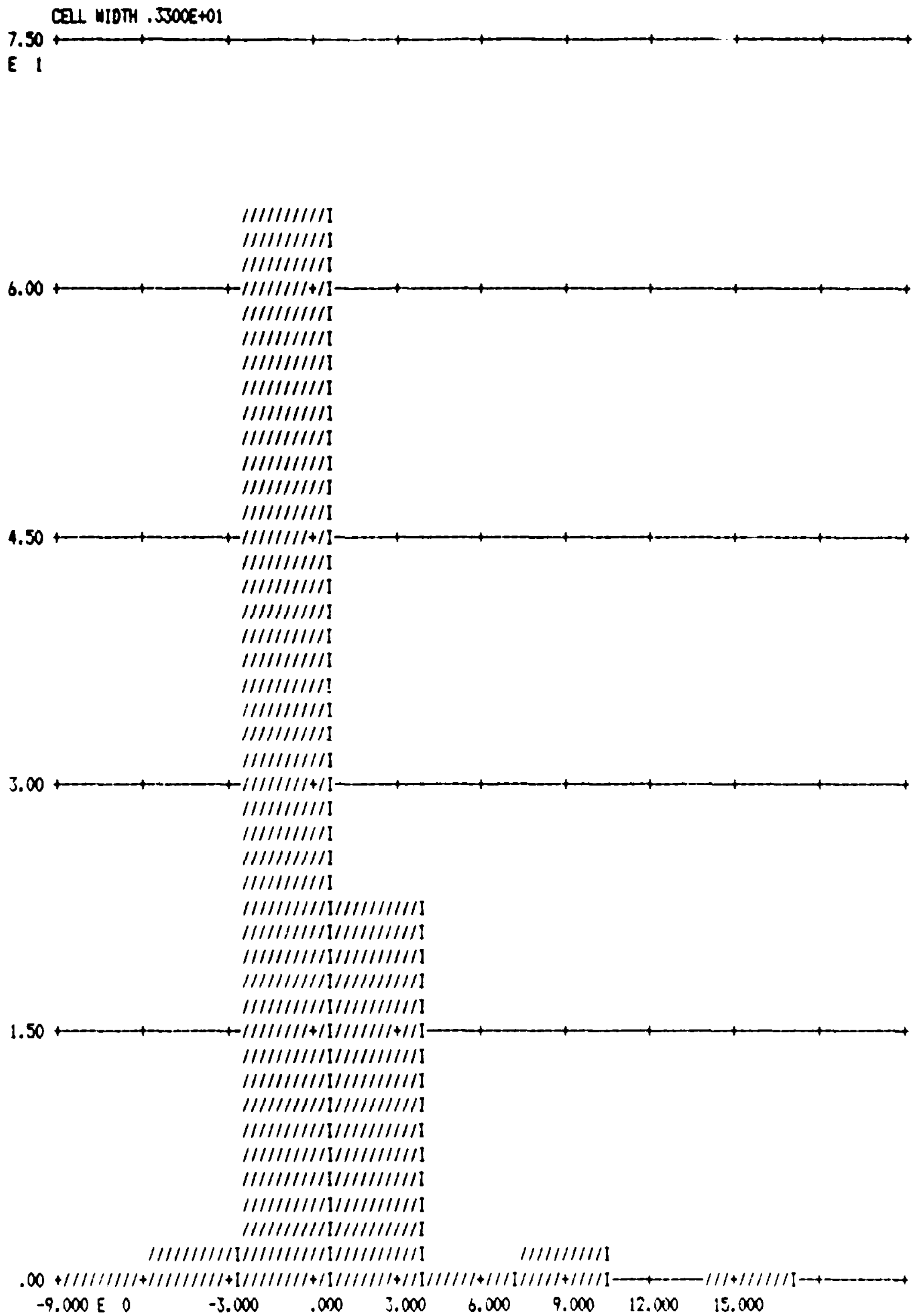

Figure C7. ASSY31 Univariate Histogram of Residuals

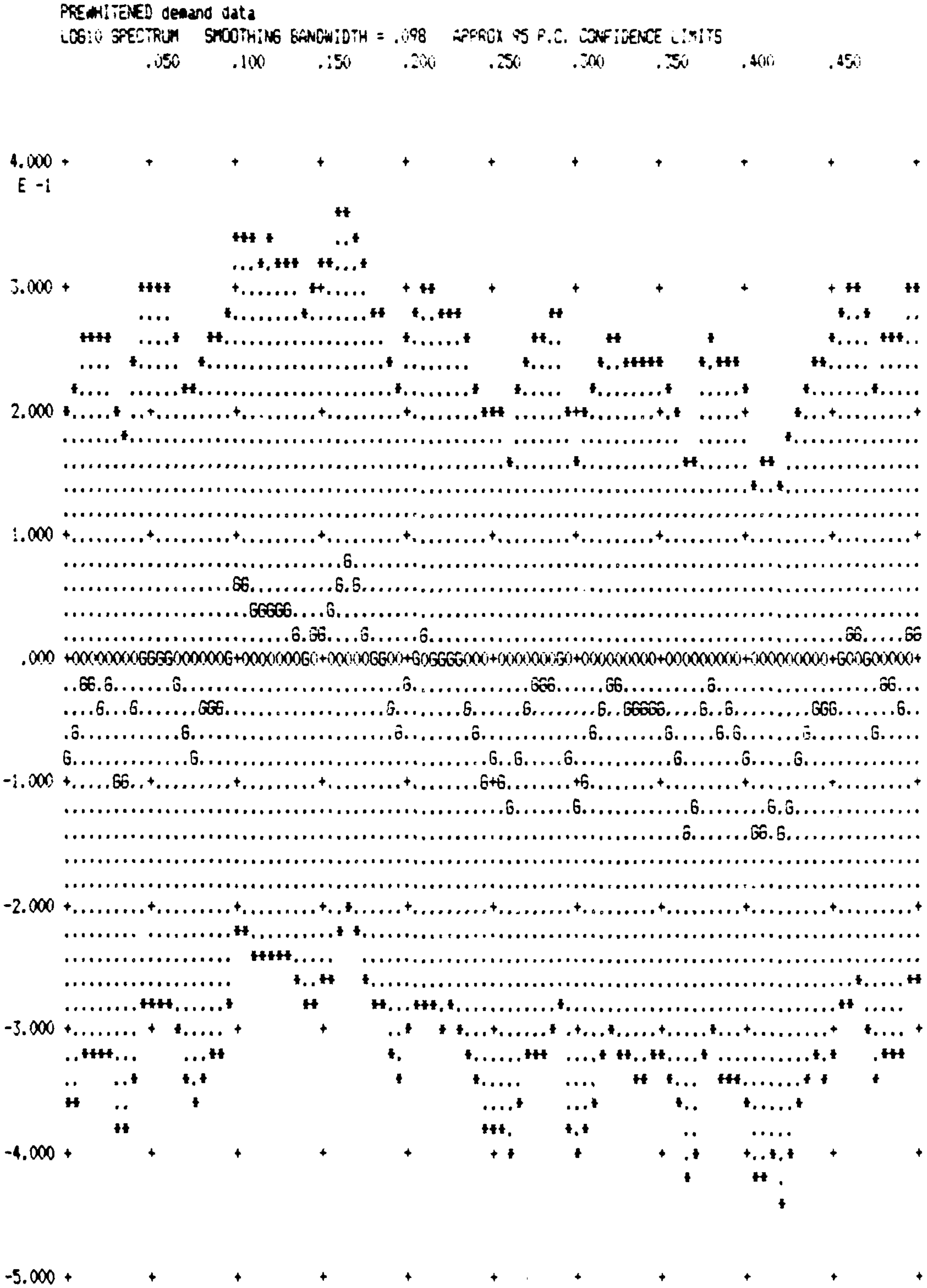

Figure C8. ASSY31 Univariate Power Spectrum

SUMMARY OF MODEL 1

```
**********************************************************************************************************************

DATA - Z = demand data                                                                              96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

**********************************************************************************************************************
```

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	MOVING AVERAGE 1	1	.14553E+00	-.57480E-01	.34854E+00
2	MOVING AVERAGE 1	5	.13526E+00	-.69389E-01	.33992E+00

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.73859E+02	93 D.F.	RESIDUAL MEAN SQUARE	.79418E+00
NUMBER OF RESIDUALS	95		RESIDUAL STANDARD ERROR	.89117E+00

Figure C9. FRAME53 Univariate Parameter Values

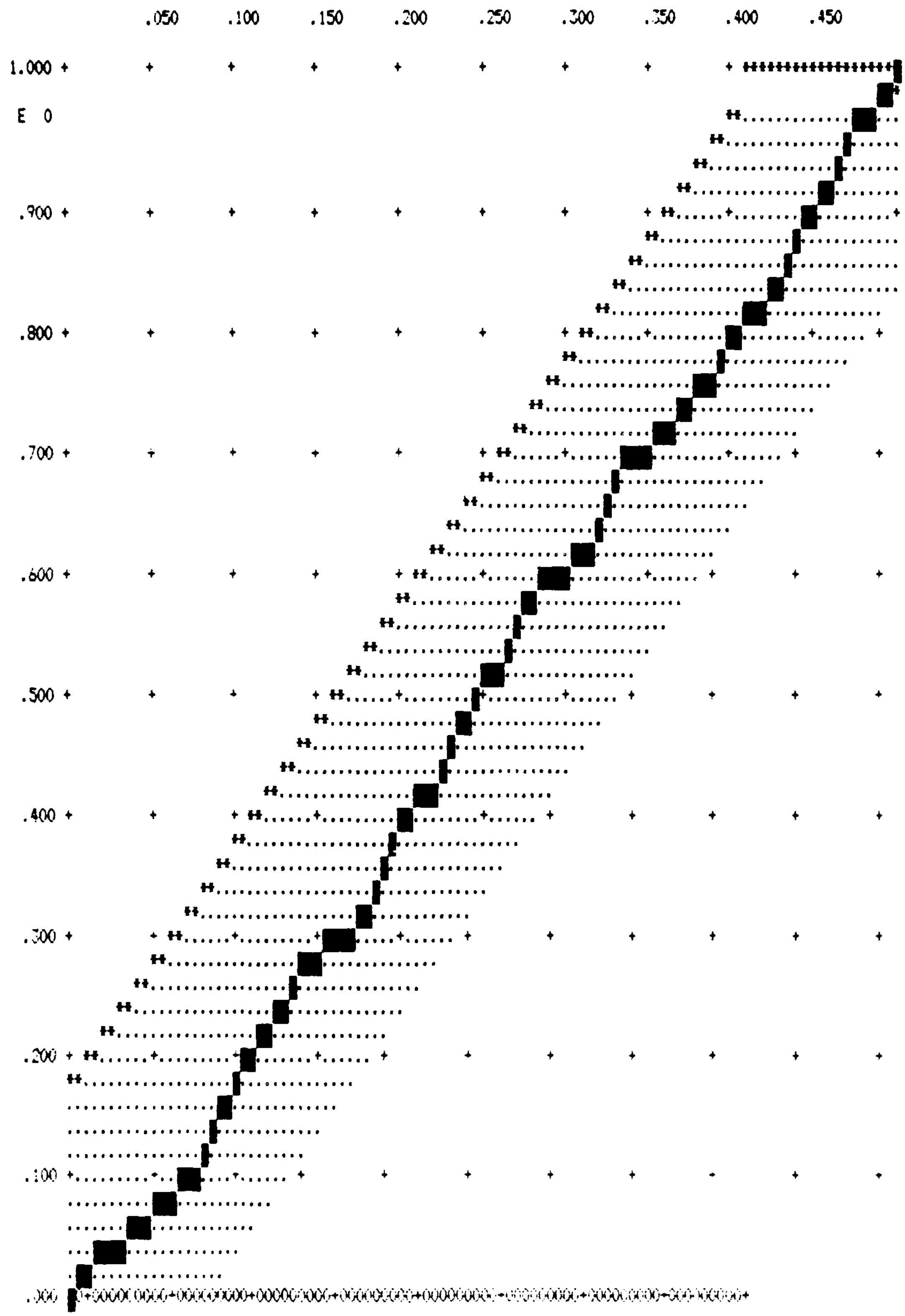

Figure C10. FRAME53 Univariate Cumulative Periodogram

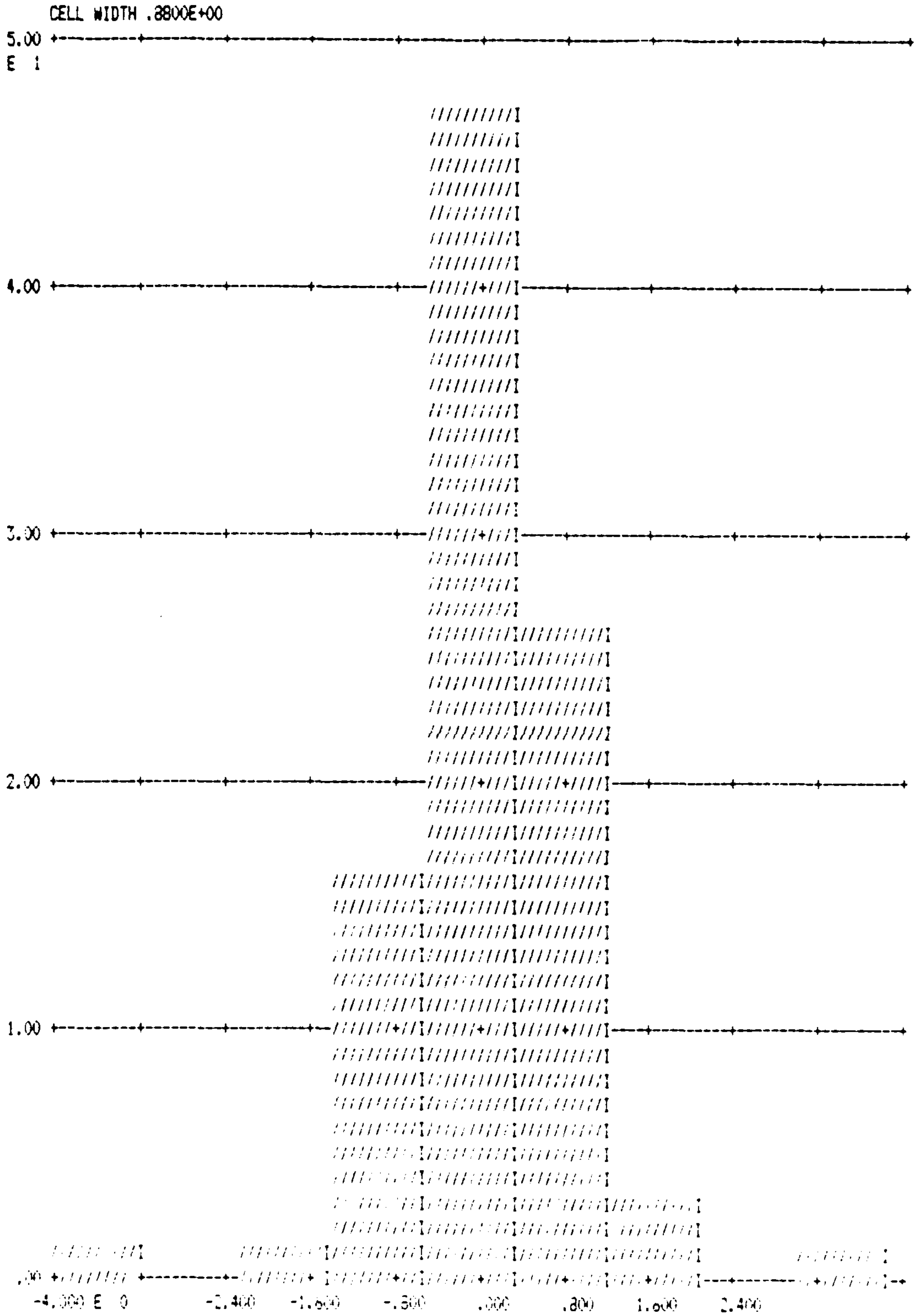

Figure C11. FRAME53 Univariate Histogram of Residuals

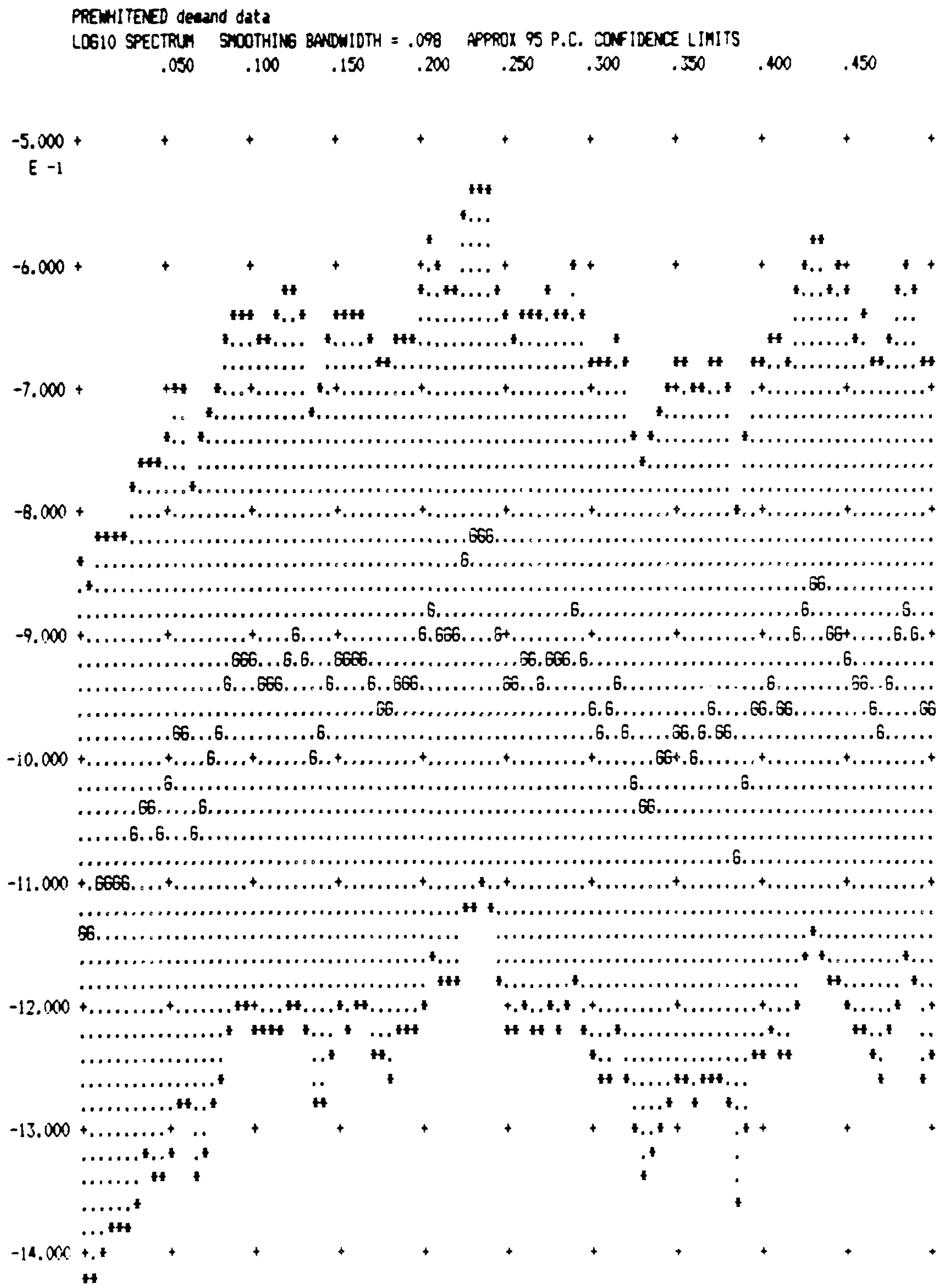

Figure C12. FRAME53 Univariate Power Spectrum

SUMMARY OF MODEL 1

++

DATA - Z = demand data 96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

++

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	MOVING AVERAGE 1	1	.77157E-01	-.12534E+00	.27965E+00
2	MOVING AVERAGE 1	3	[illegible]	-.33692E+00	.71872E-01
3	MOVING AVERAGE 1	6	.23670E+00	.32123E-01	.44127E+00

++

OTHER INFORMATION AND RESULTS

++

RESIDUAL SUM OF SQUARES	.17554E+03	92 D.F.	RESIDUAL MEAN SQUARE	.19081E+01
NUMBER OF RESIDUALS	95		RESIDUAL STANDARD ERROR	.13813E+01

Figure C13. TAIL84 Univariate Parameter Values

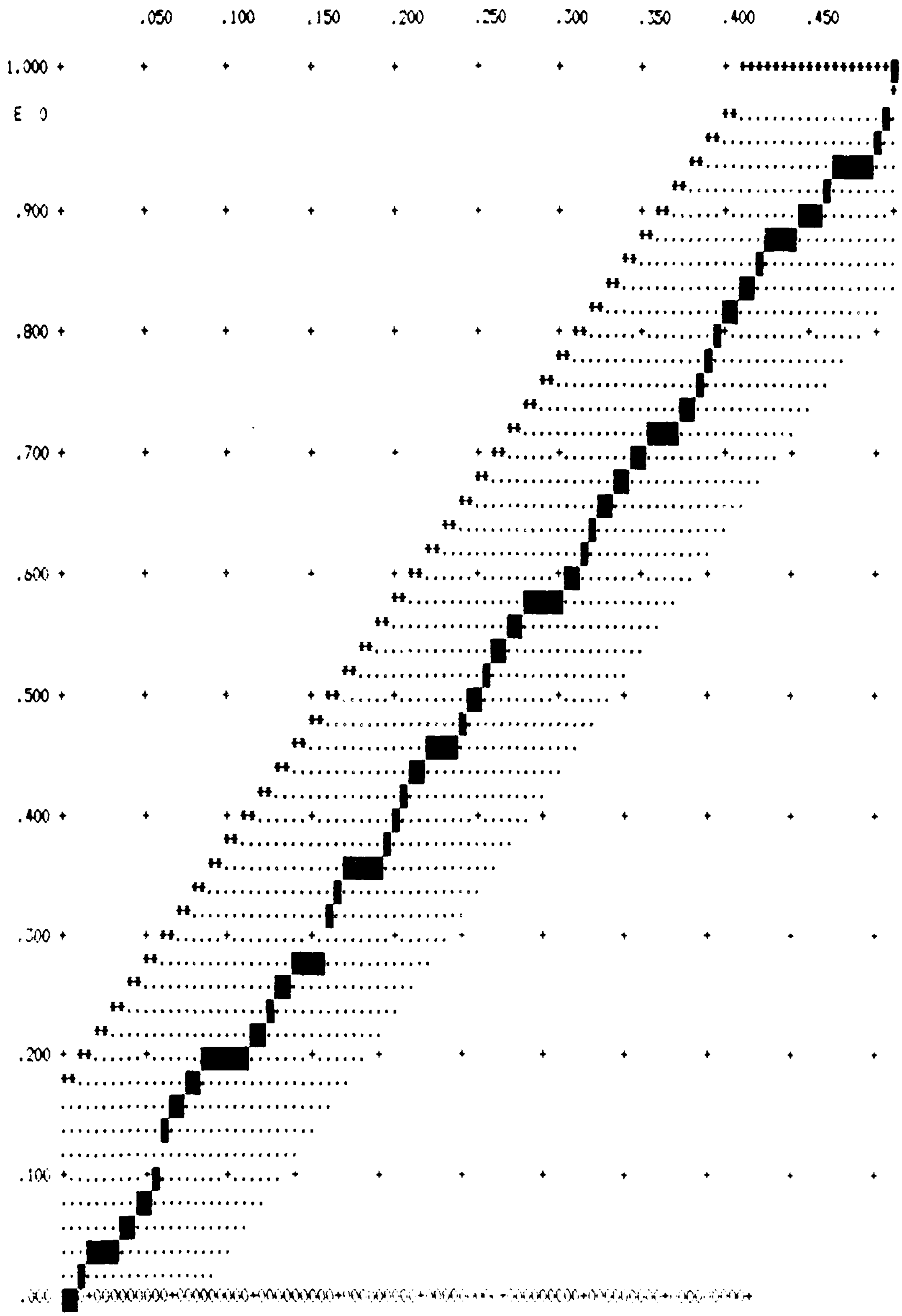

Figure C14. TAIL84 Univariate Cumulative Periodogram

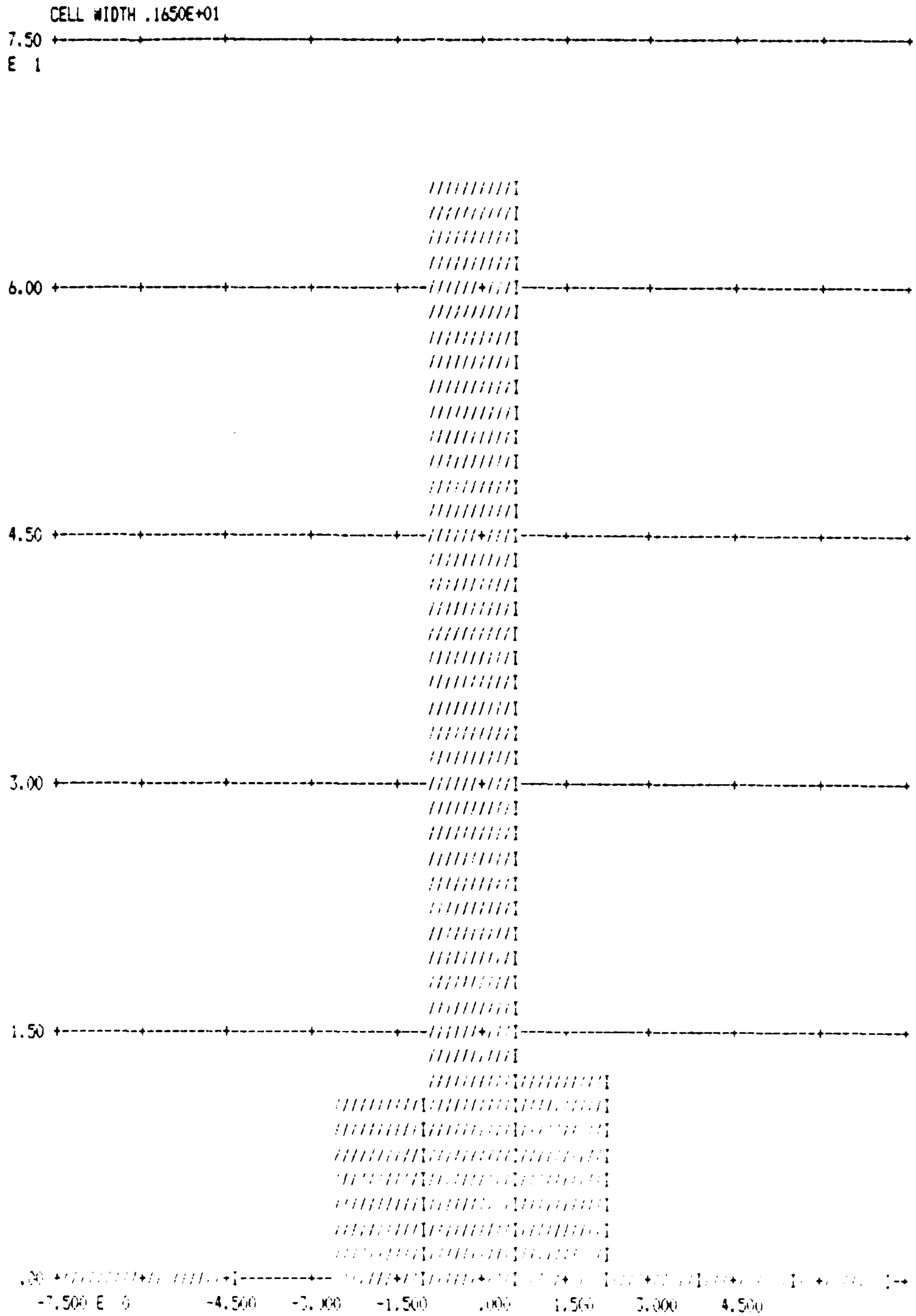

Figure C15. TAIL84 Univariate Histogram of Residuals

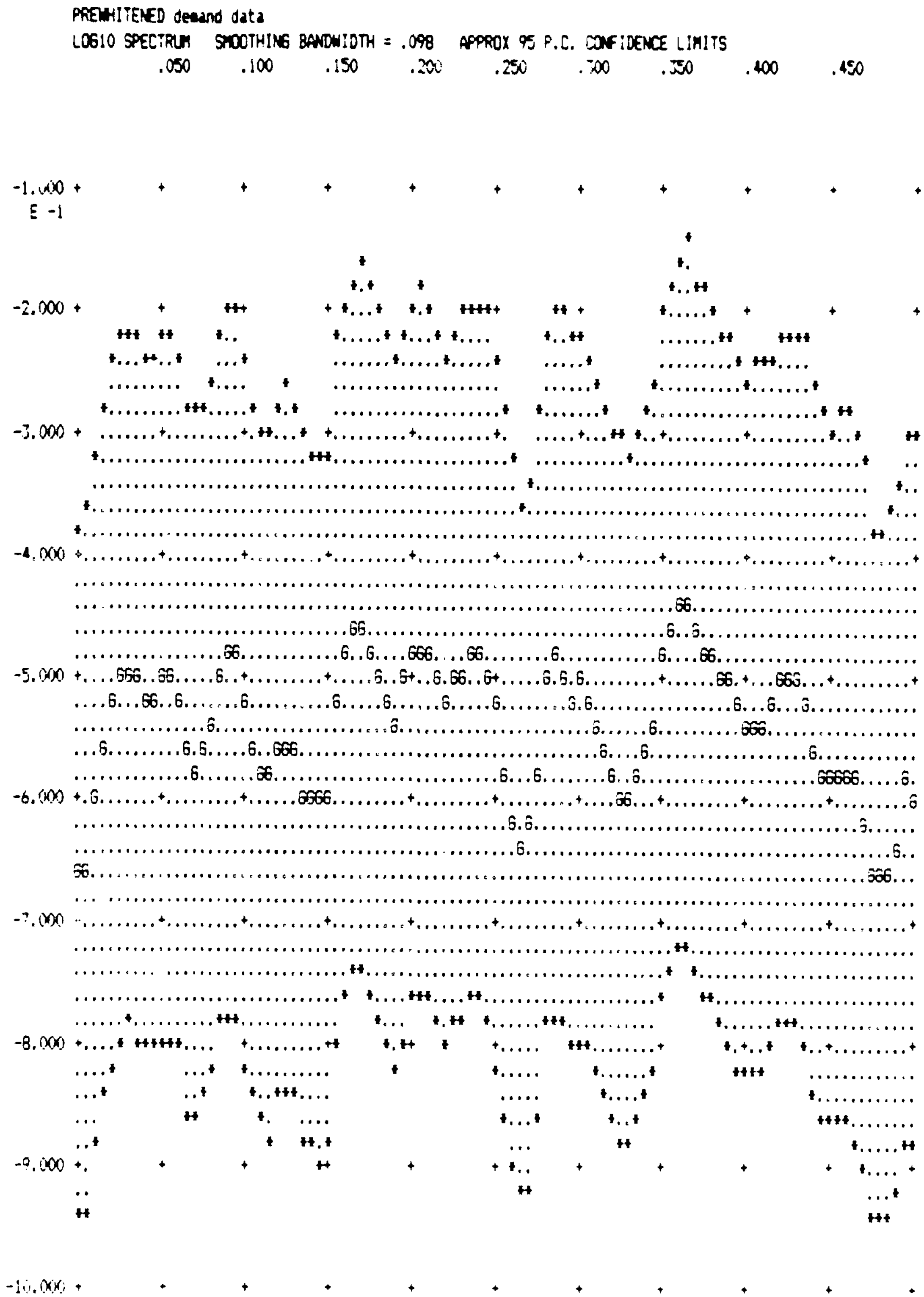

Figure C16. TAIL84 Univariate Power Spectrum

SUMMARY OF MODEL 1

##

DATA - Z = demand data cowl83 96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

##

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.11556E+00	-.32783E+00	.96712E-01
2	AUTOREGRESSIVE 1	2	-.12574E+00	-.33792E+00	.86439E-01
3	MOVING AVERAGE 1	3	-.21218E+00	-.42684E+00	.24768E-02
4	MOVING AVERAGE 1	6	-.11390E+00	-.32563E+00	.97823E-01

##

OTHER INFORMATION AND RESULTS

##

RESIDUAL SUM OF SQUARES .70903E+02 89 D.F. RESIDUAL MEAN SQUARE .79666E+00

NUMBER OF RESIDUALS 93 RESIDUAL STANDARD ERROR .89256E+00

Figure C17. COWL83 Univariate Parameter Values

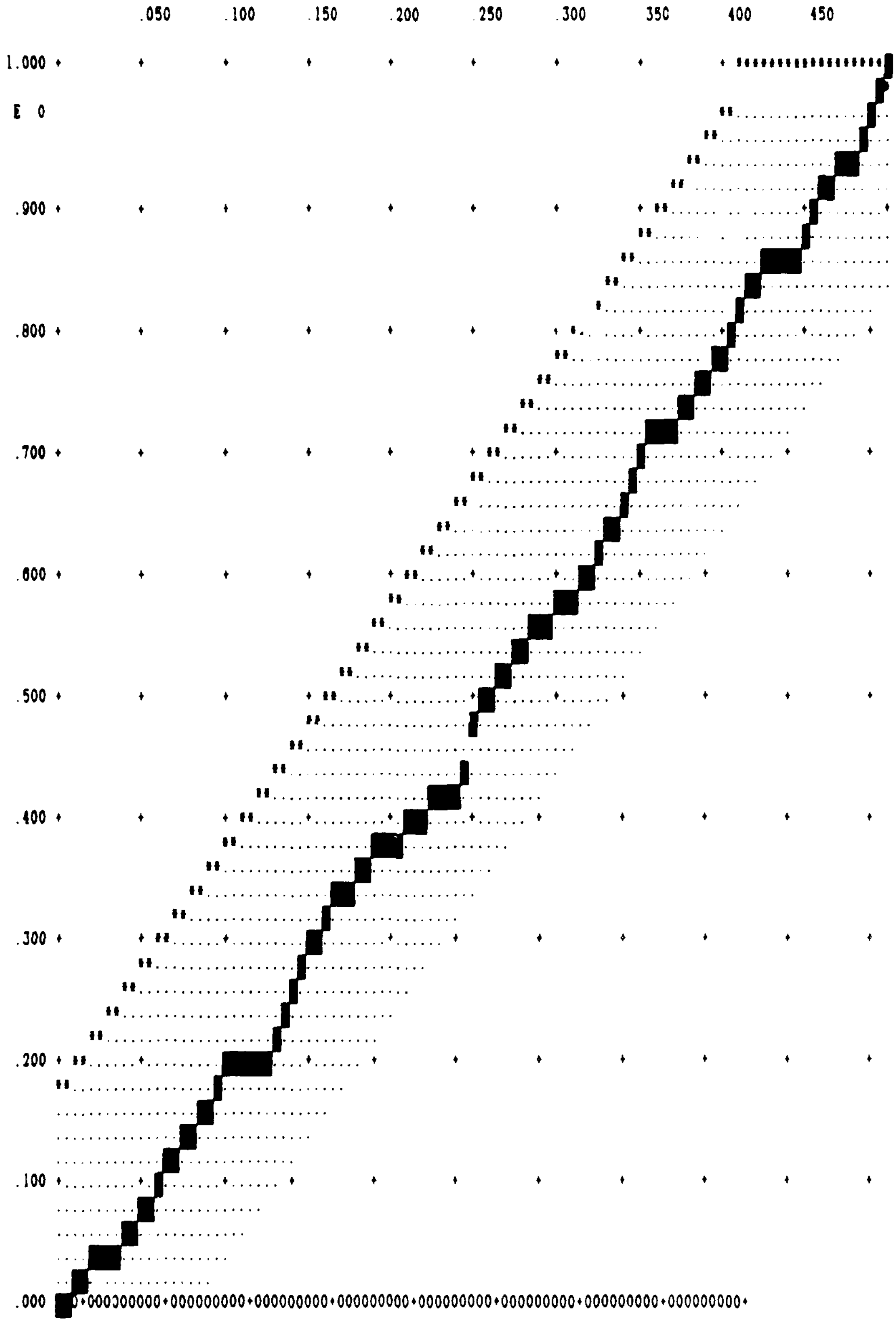

Figure C18. COWL83 Univariate Cumulative Periodogram

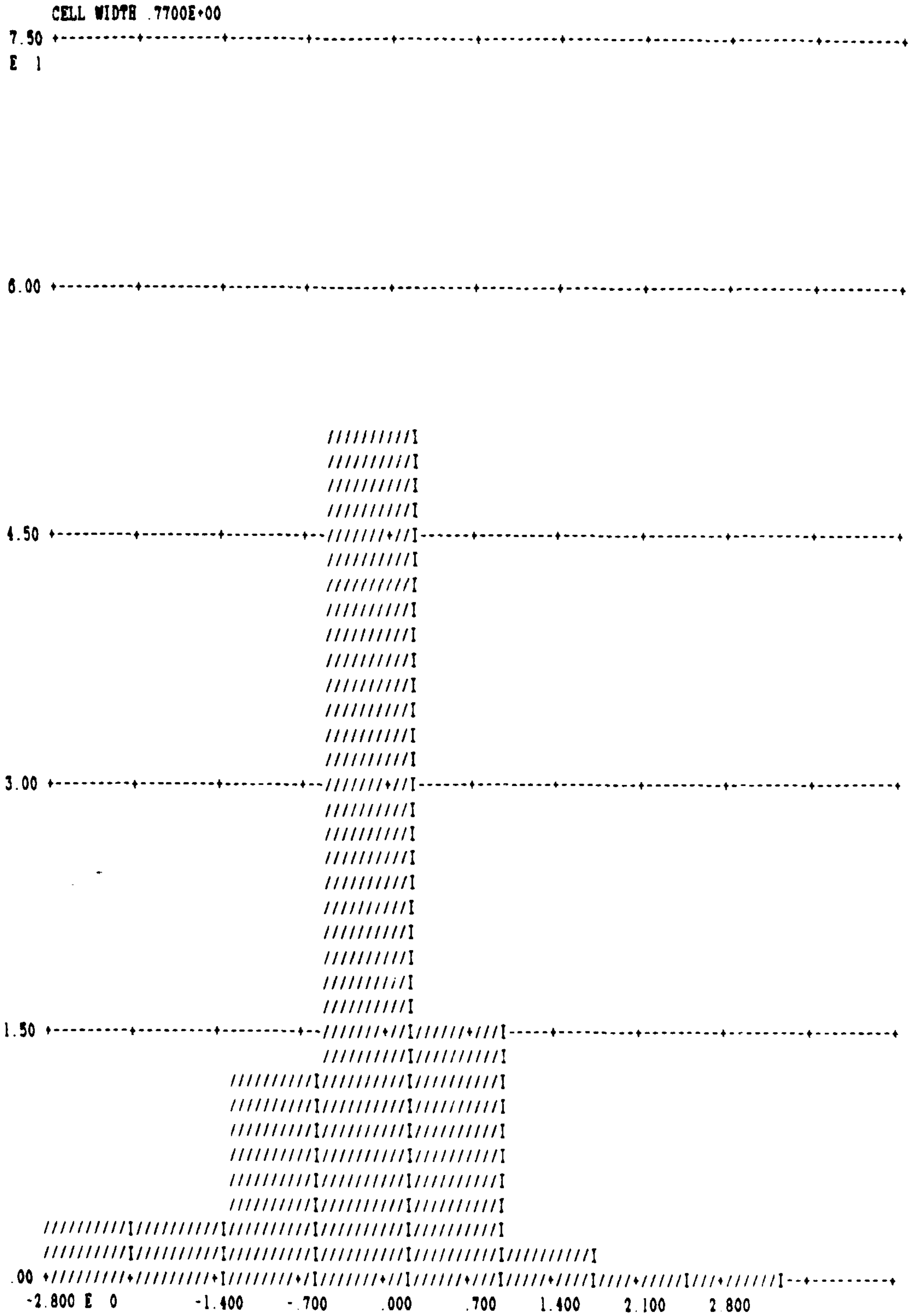

Figure C19. COWL83 Univariate Histogram of Residuals

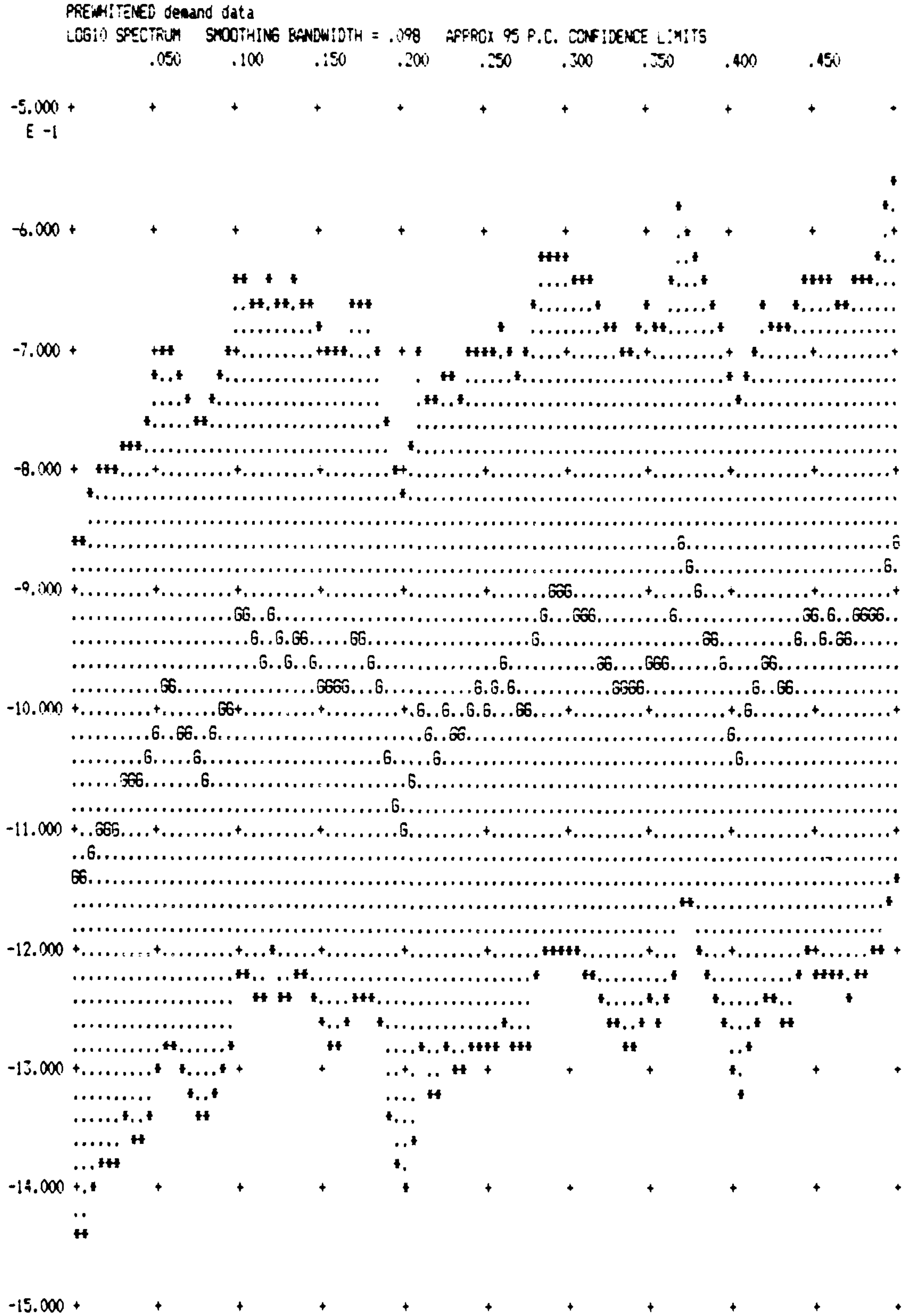

Figure C20. COWL83 Univariate Power Spectrum

SUMMARY OF MODEL 1

##

DATA - Z = demand data slve85 96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

##

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	1	-.34146E-01	-.23550E+00	.16721E+00
2	AUTOREGRESSIVE 1	3	.32926E+00	.11681E+00	.54171E+00
3	MOVING AVERAGE 1	2	.83231E-01	-.12945E+00	.29591E+00
4	MOVING AVERAGE 1	6	-.49543E-01	-.27529E+00	.17620E+00

##

OTHER INFORMATION AND RESULTS

##

RESIDUAL SUM OF SQUARES .11572E+03 88 D.F. RESIDUAL MEAN SQUARE .13150E+01

NUMBER OF RESIDUALS 92 RESIDUAL STANDARD ERROR .11467E+01

Figure C21. SLVE85 Univariate Parameter Values

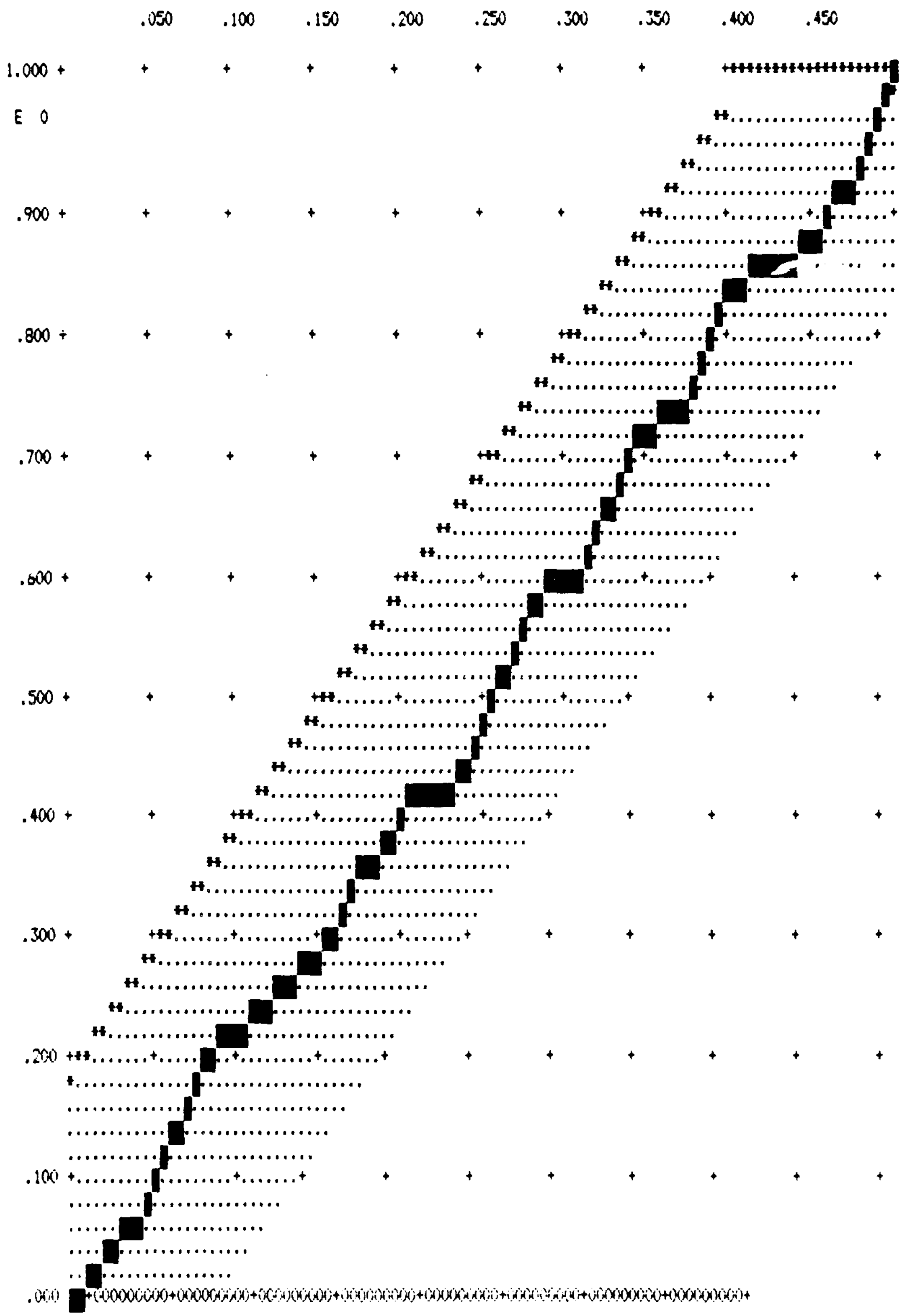

Figure C22. SLVE85 Univariate Cumulative Periodogram

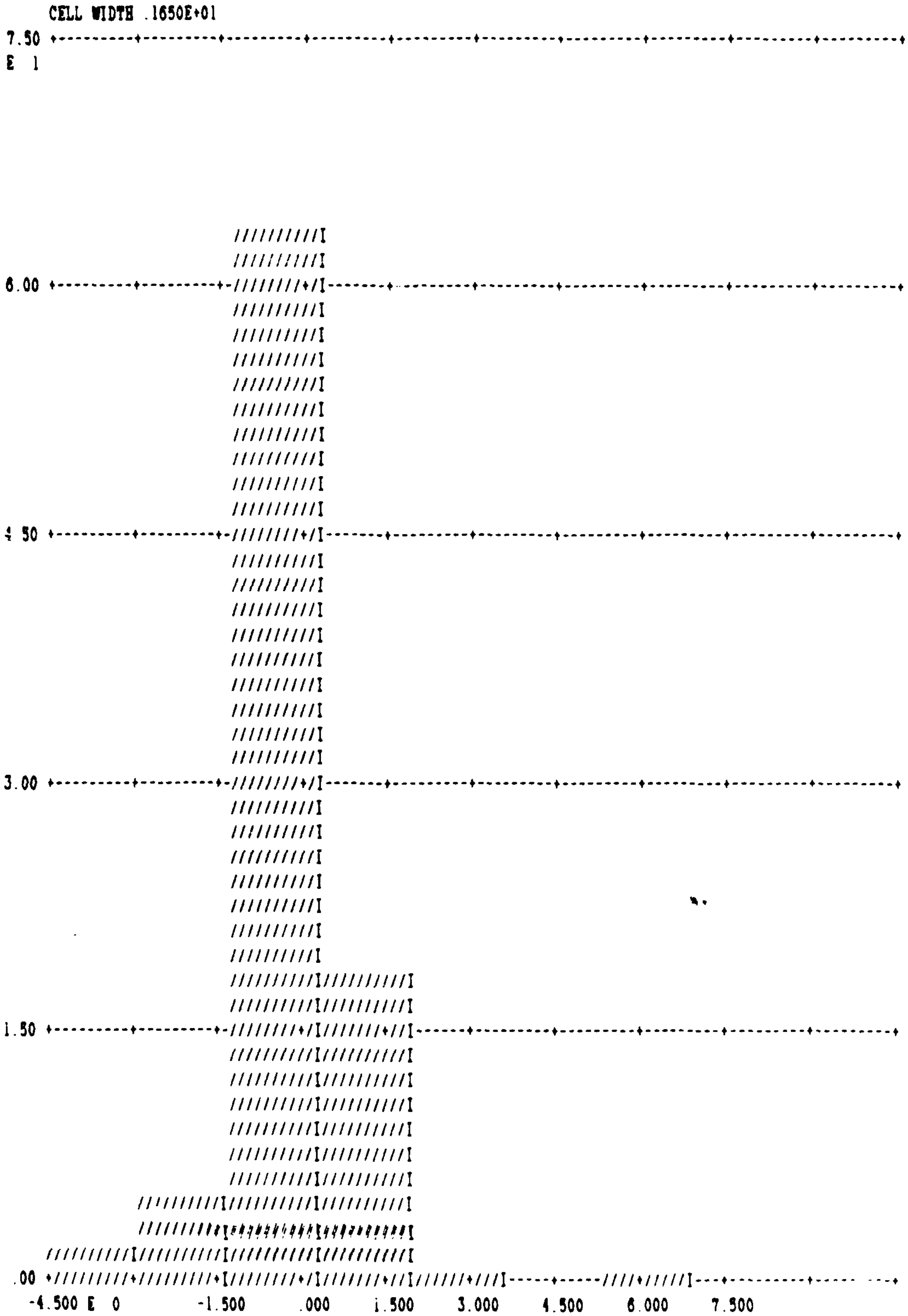

Figure C23. SLVE85 Univariate Histogram of Residuals

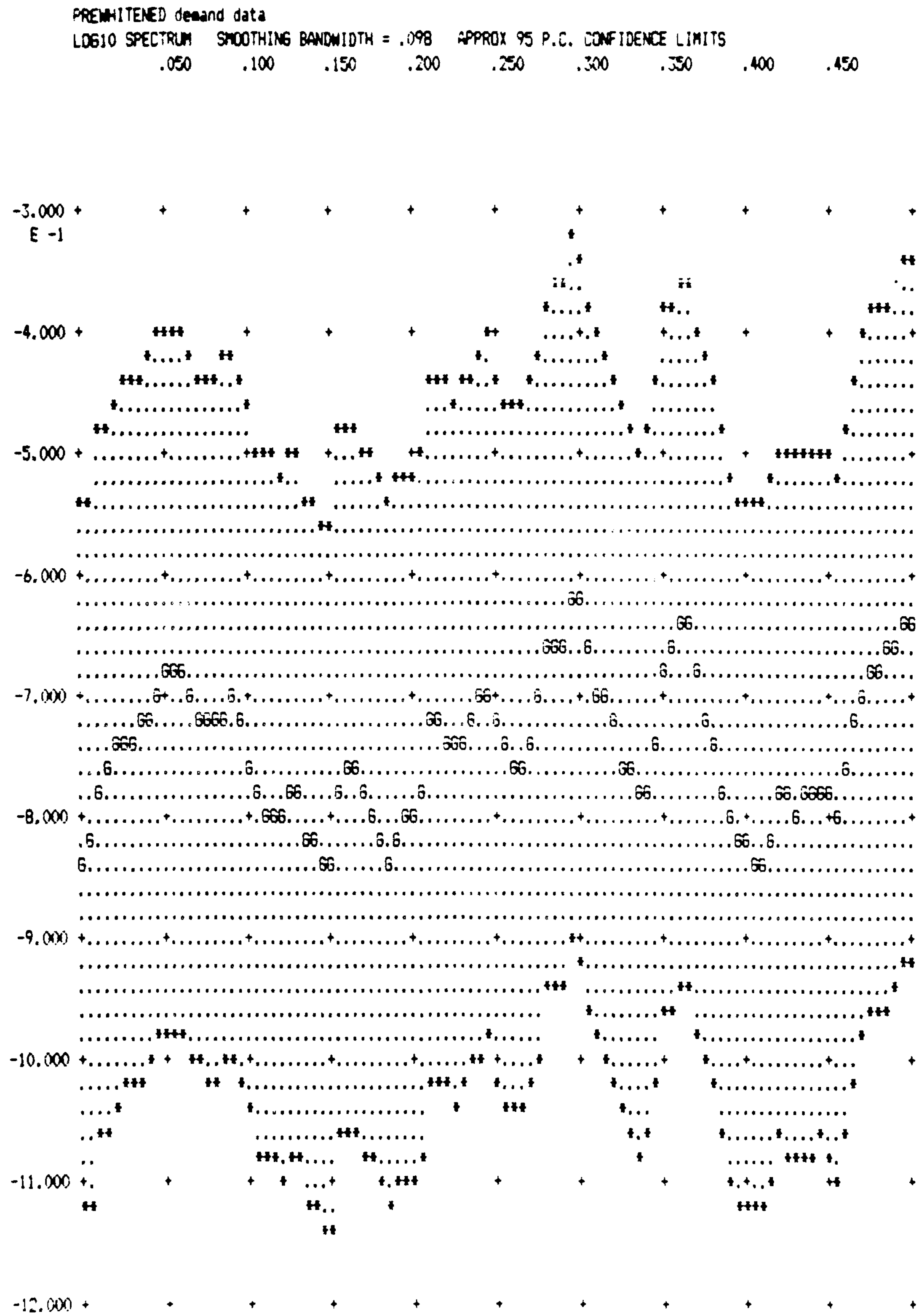

Figure C24. SLVE85 Univariate Power Spectrum

```
SUMMARY OF MODEL  1

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

DATA - Z = demand data                                                                      96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER  1

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

PARAMETER          PARAMETER          PARAMETER      ESTIMATED                 95 PER CENT
 NUMBER              TYPE               ORDER          VALUE        . LOWER LIMIT         UPPER LIMIT

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

   1            MOVING AVERAGE 1          3         -.38288E+00     -.57397E+00          -.19179E+00

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

OTHER INFORMATION AND RESULTS

++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

RESIDUAL SUM OF SQUARES      .14529E+04    94 D.F.           RESIDUAL MEAN SQUARE              .15456E+02

NUMBER OF RESIDUALS                  95                      RESIDUAL STANDARD ERROR           .39314E+01
```

Figure C25. ASSY32 Univariate Parameter Values

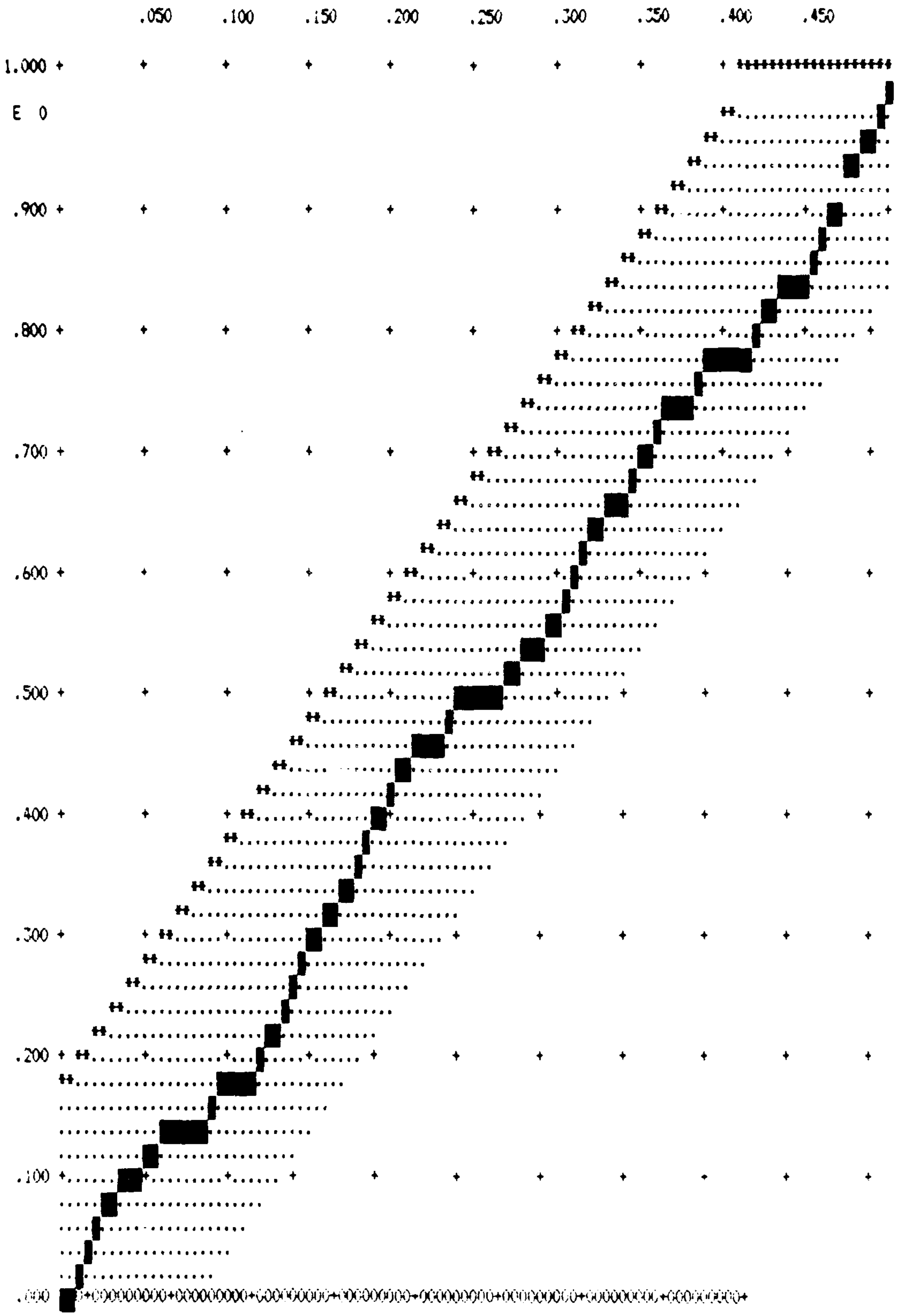

Figure C26. ASSY32 Univariate Cumulative Periodogram

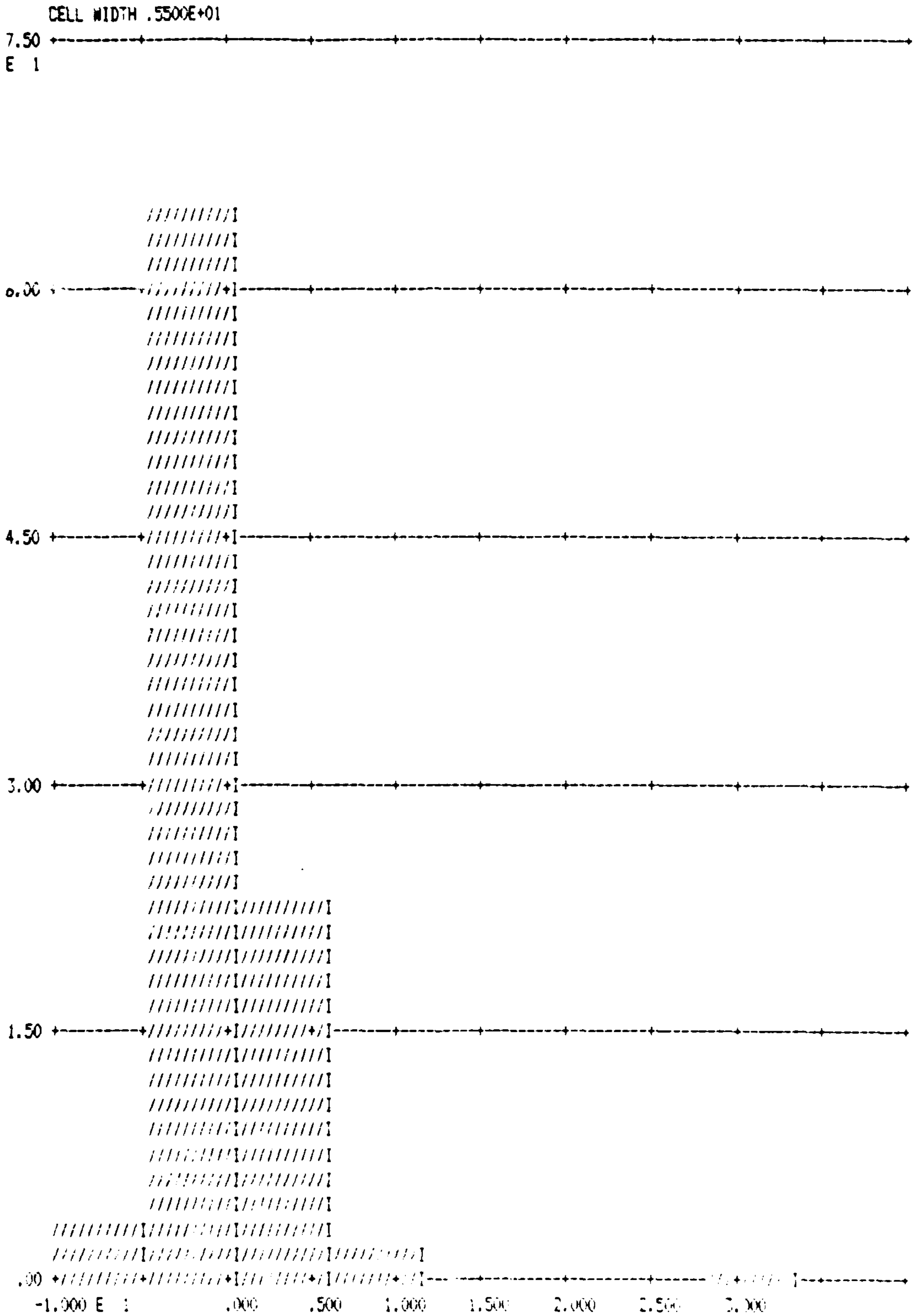

Figure C27. ASSY32 Univariate Histogram of Residuals

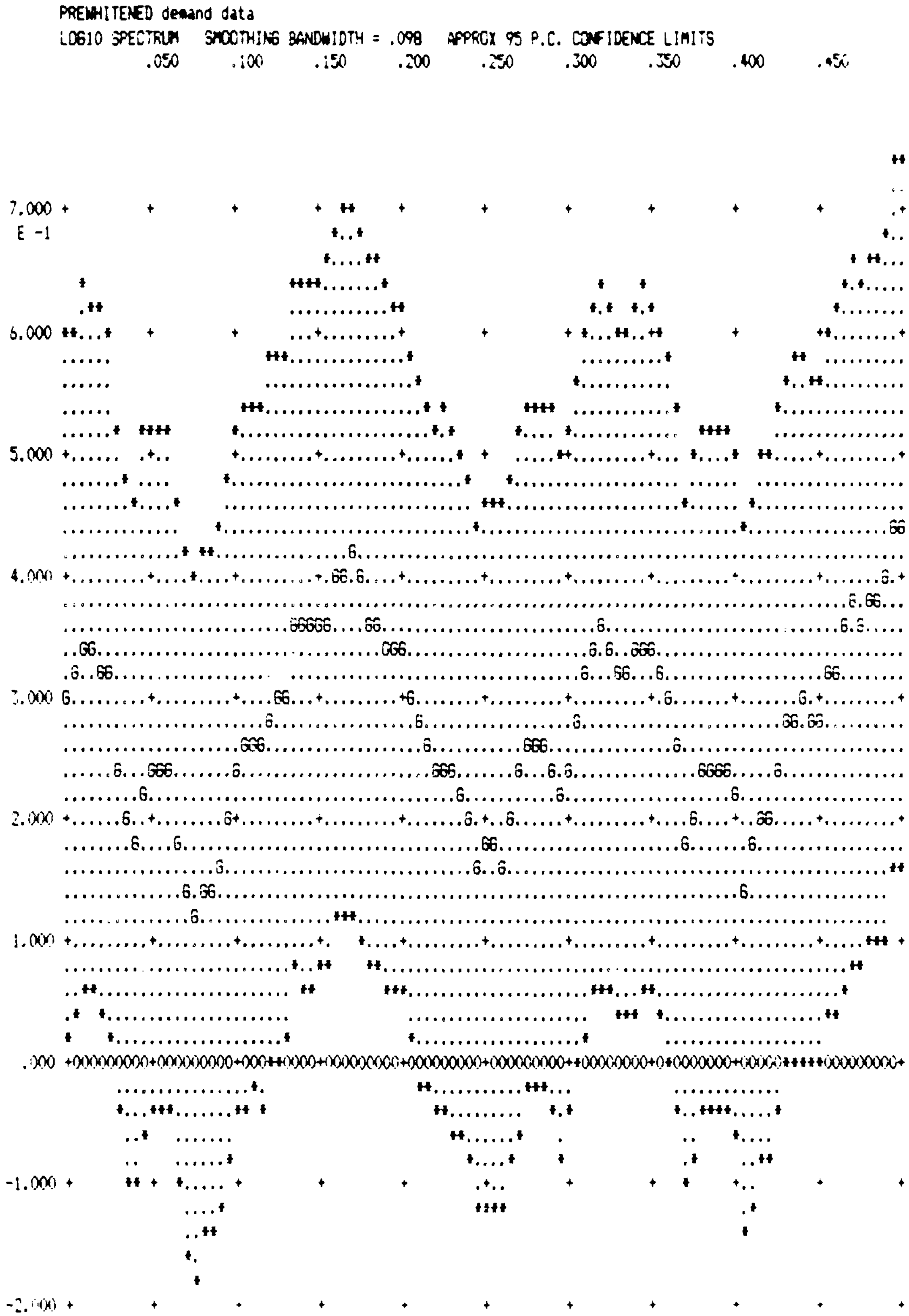

Figure C28. ASSY32 Univariate Power Spectrum

```
SUMMARY OF MODEL  1

**************************************************************************************************

DATA - Z = demand data                                                            96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER  1

**************************************************************************************************

PARAMETER          PARAMETER          PARAMETER     ESTIMATED               95 PER CENT
 NUMBER              TYPE               ORDER         VALUE         LOWER LIMIT        UPPER LIMIT

**************************************************************************************************

   1            MOVING AVERAGE 1          6        -.41263E+00      -.61435E+00        -.21091E+00

**************************************************************************************************

OTHER INFORMATION AND RESULTS

**************************************************************************************************

RESIDUAL SUM OF SQUARES     .90629E+03    94 D.F.          RESIDUAL MEAN SQUARE            .96413E+01

NUMBER OF RESIDUALS              95                        RESIDUAL STANDARD ERROR         .31051E+01
```

Figure C29. ASSY33 Univariate Parameter Values

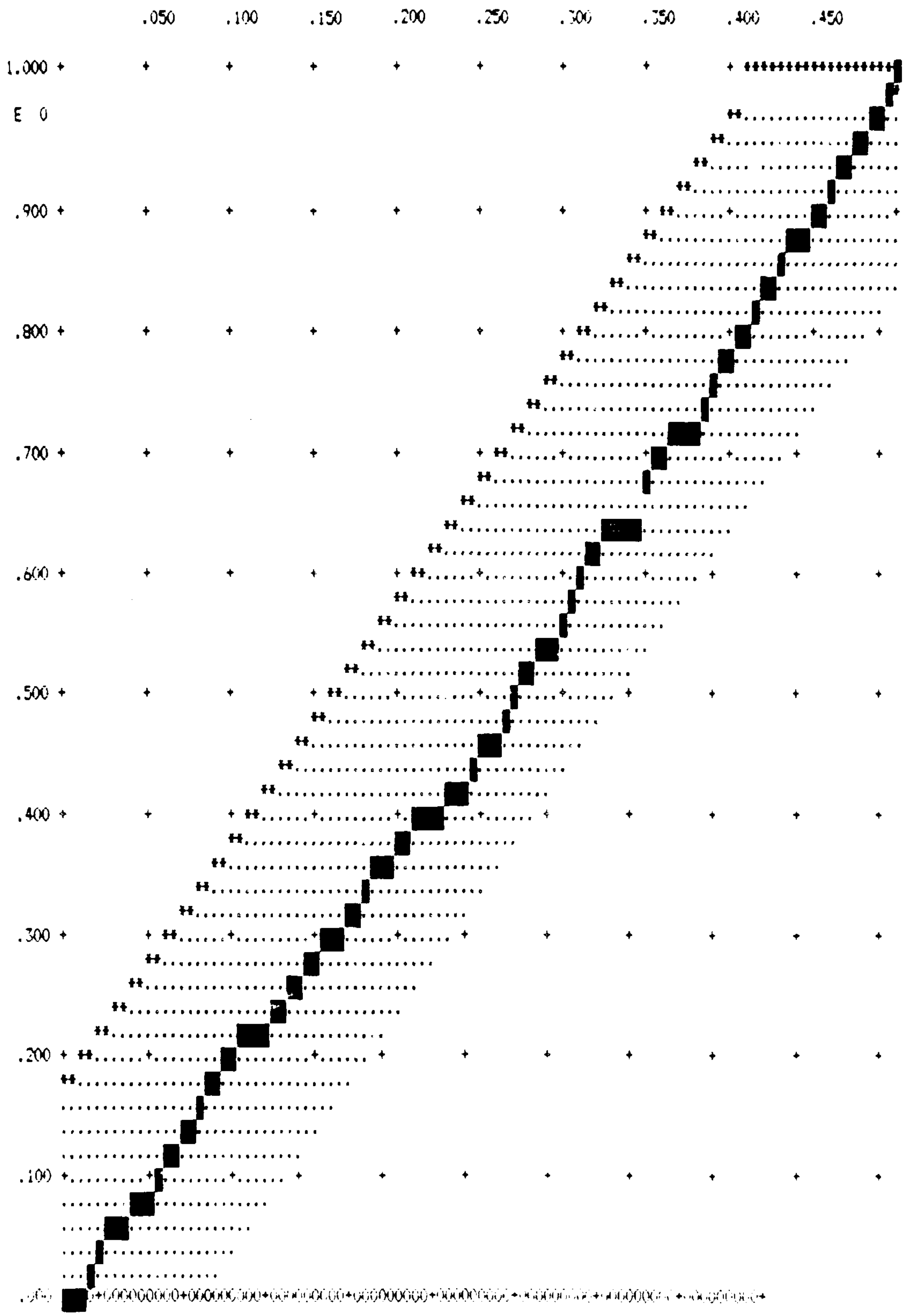

Figure C30. ASSY33 Univariate Cumulative Periodogram

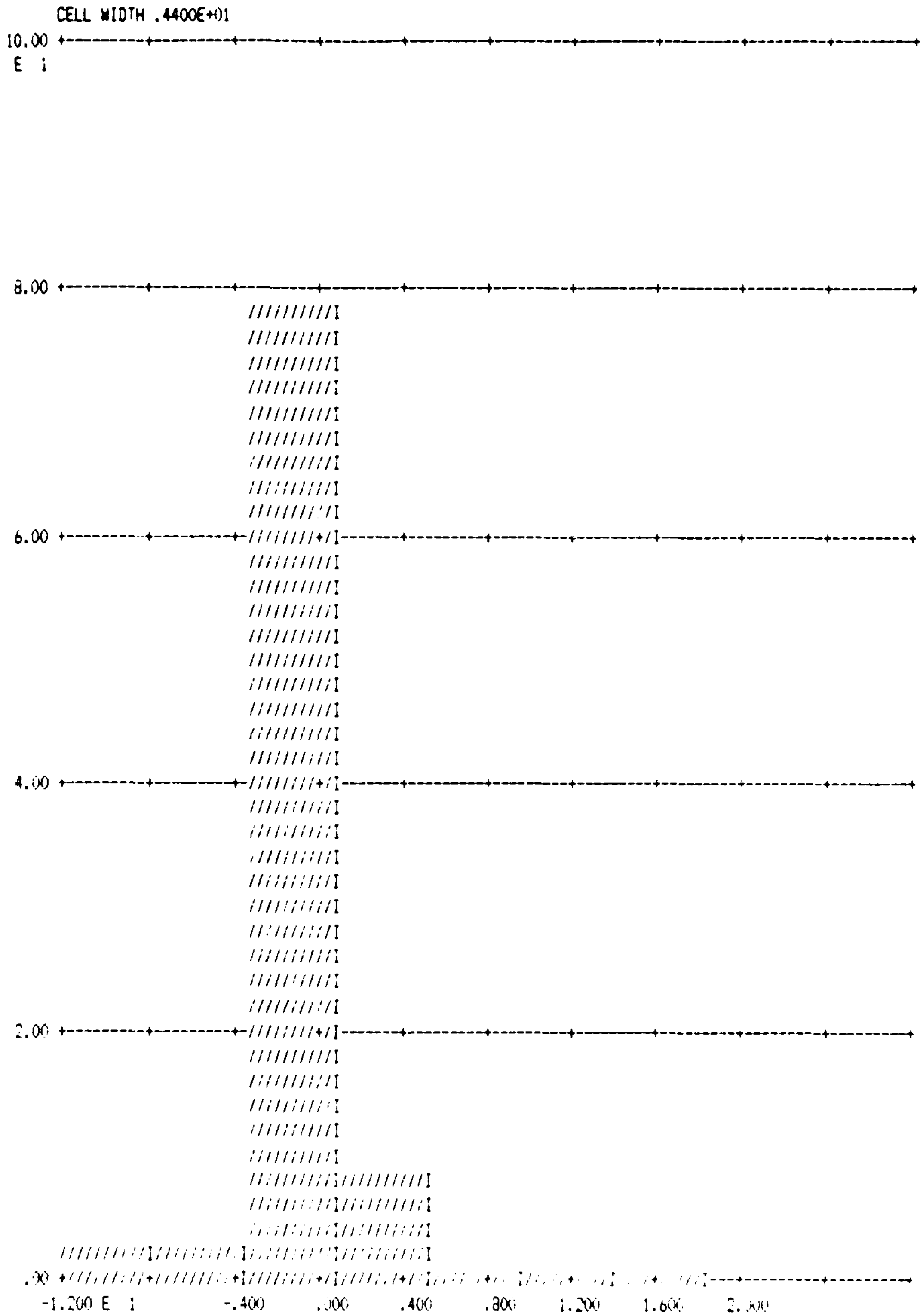

Figure C31. ASSY33 Univariate Histogram of Residuals

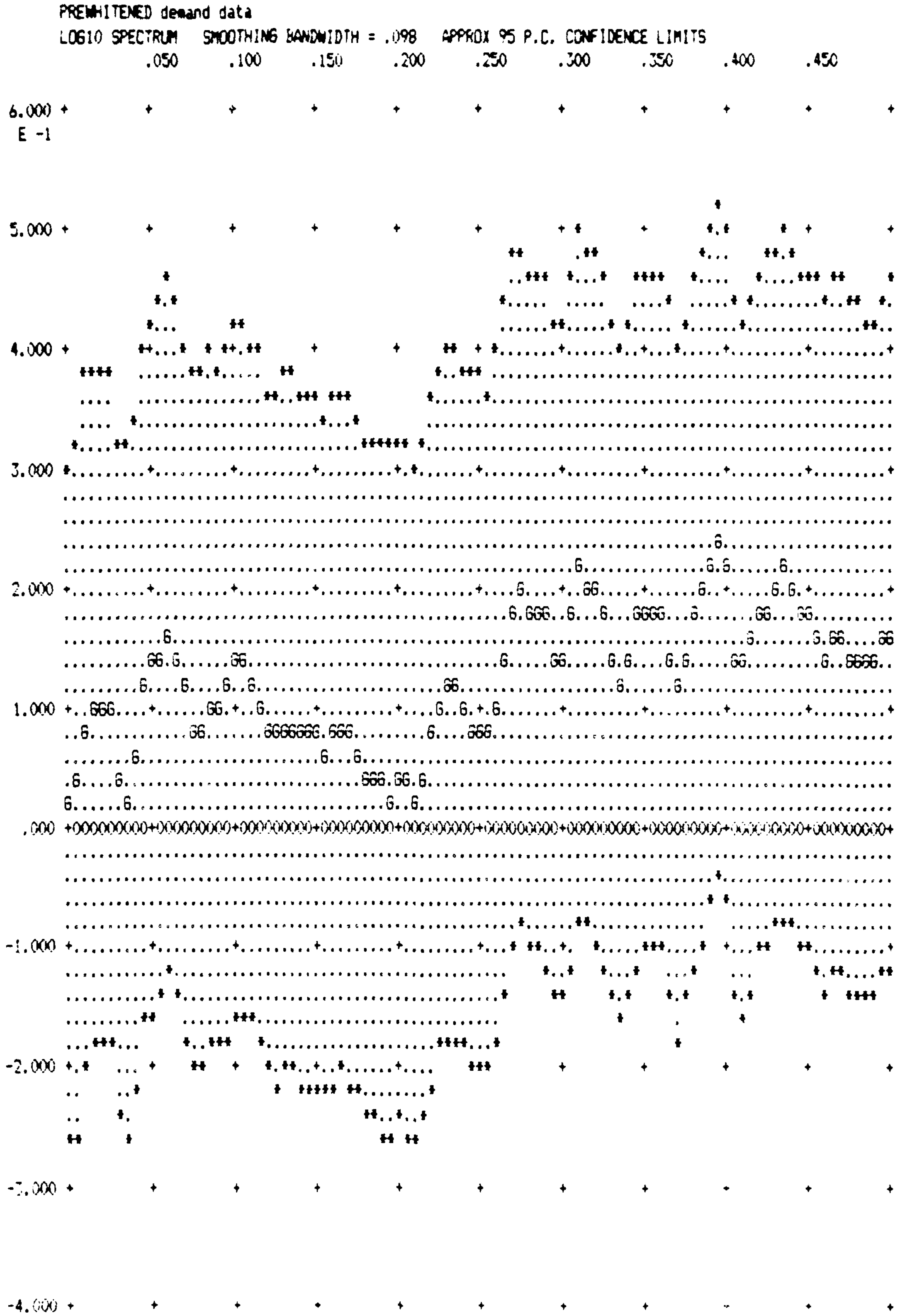

Figure C32. ASSY33 Univariate Power Spectrum

SUMMARY OF MODEL 1

DATA - Z = demand data 96 OBSERVATIONS

DIFFERENCING ON Z - 1 OF ORDER 1

PARAMETER NUMBER	PARAMETER TYPE	PARAMETER ORDER	ESTIMATED VALUE	95 PER CENT LOWER LIMIT	95 PER CENT UPPER LIMIT
1	AUTOREGRESSIVE 1	3	.82320E-01	-.13974E+00	.30439E+00
2	AUTOREGRESSIVE 1	4	-.14290E+00	-.36298E+00	.77167E-01
3	MOVING AVERAGE 1	1	.16310E+00	-.47618E-01	.37381E+00
4	MOVING AVERAGE 1	2	.11191E+00	-.10317E+00	.32698E+00
5	MOVING AVERAGE 1	6	-.28191E+00	-.52451E+00	-.39305E-01

OTHER INFORMATION AND RESULTS

RESIDUAL SUM OF SQUARES	.94479E+02	86 D.F.	RESIDUAL MEAN SQUARE	.10986E+01
NUMBER OF RESIDUALS	91		RESIDUAL STANDARD ERROR	.10481E+01

Figure C33. FORK35 Univariate Parameter Values

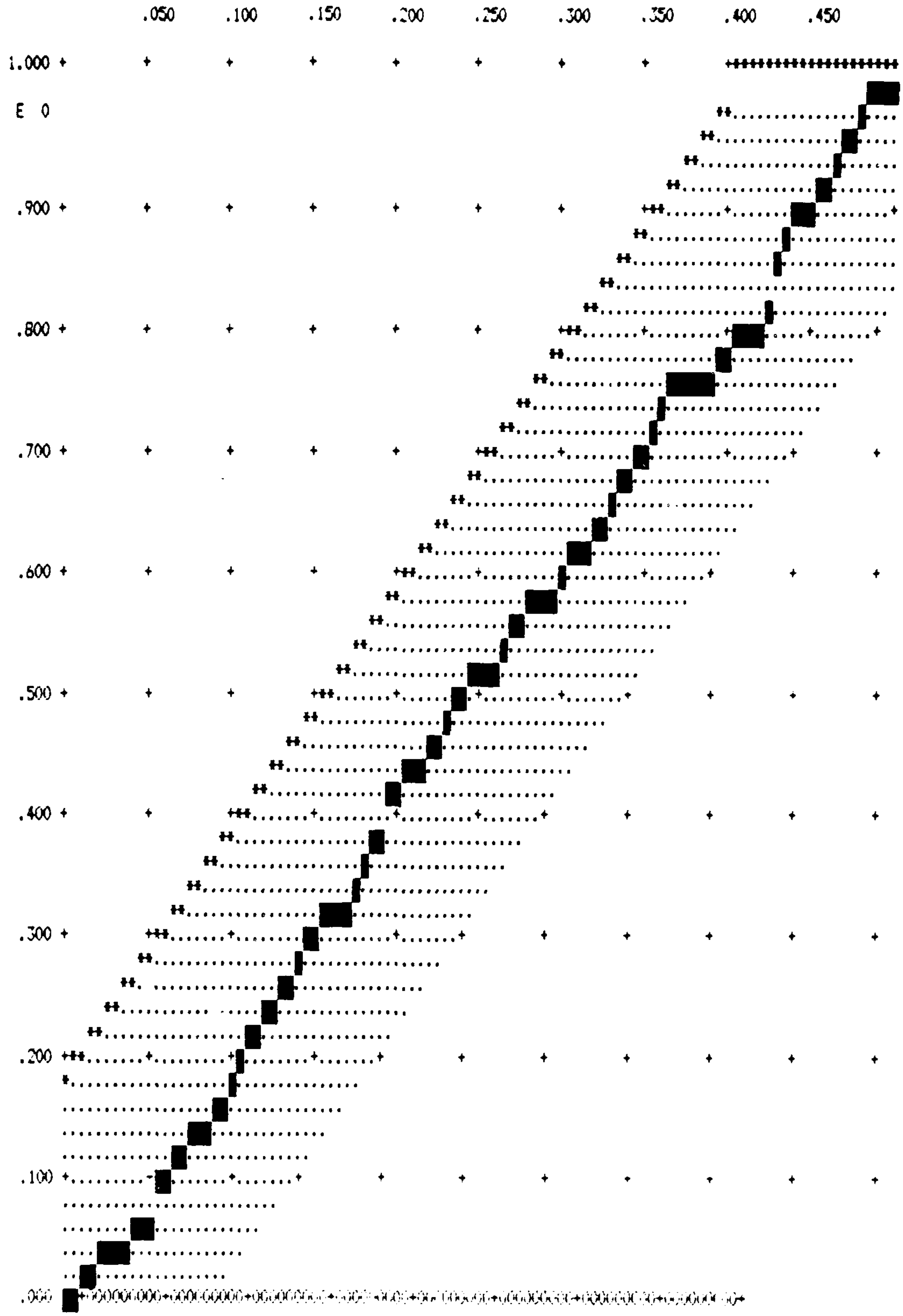

Figure C34. FORK35 Univariate Cumulative Periodogram

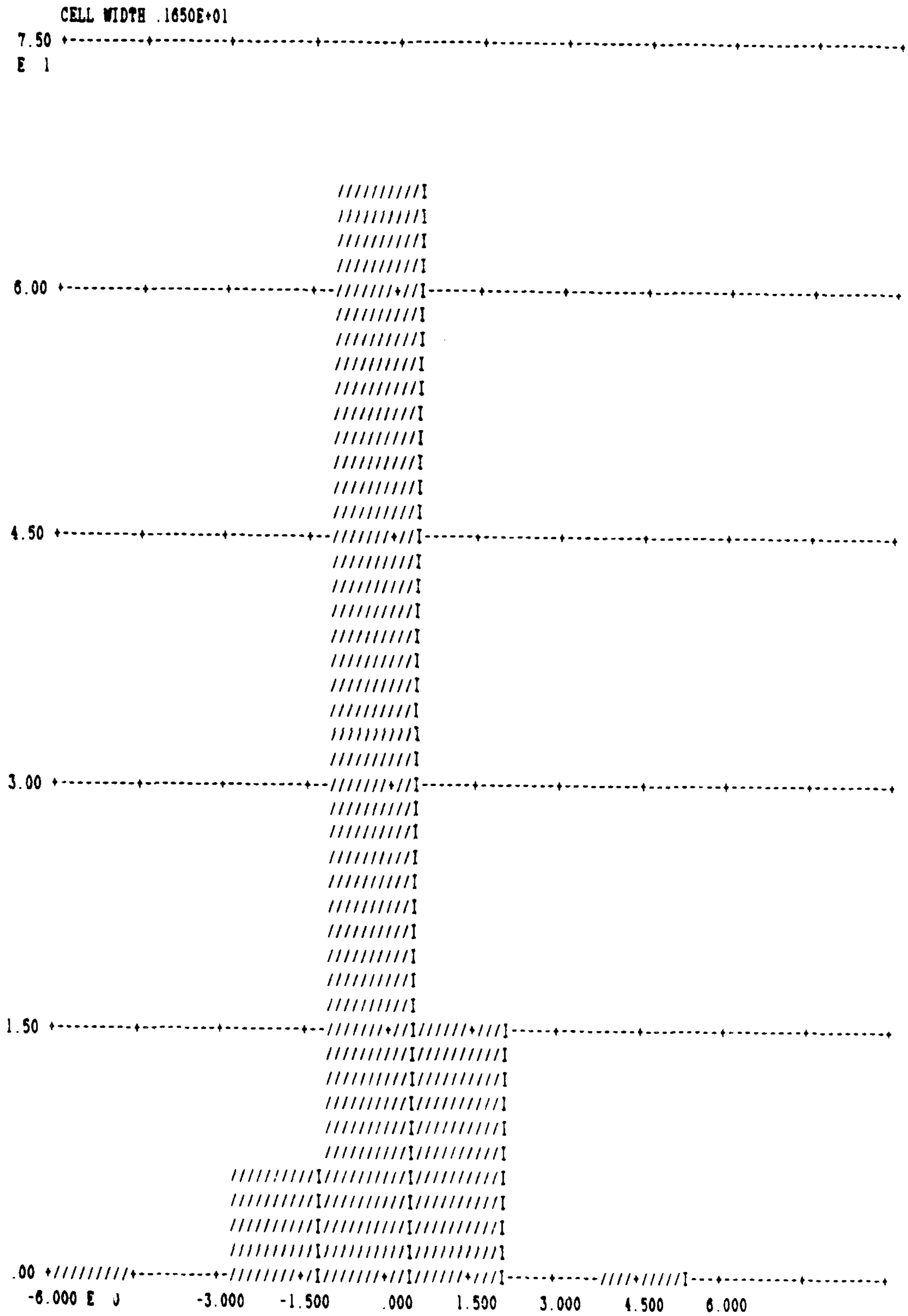

Figure C35. FORK35 Univariate Histogram of Residuals

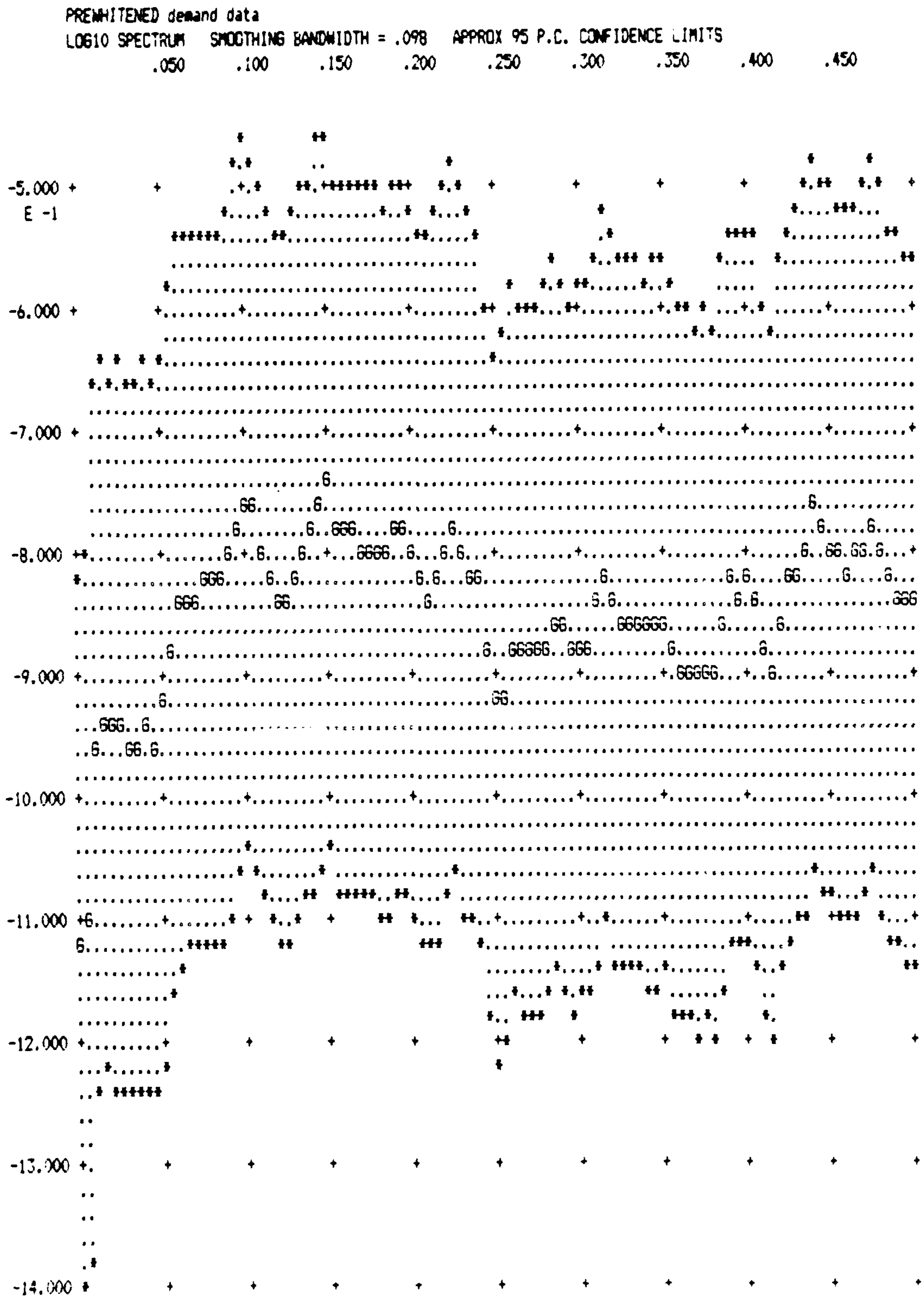

Figure C36. FORK35 Univariate Power Spectrum

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In recent years, Air Staff directed a comprehensive review of recoverable spares forecasting due to significant underestimates of spares requirements. The purpose of this study was to determine if time series forecasting models could accurately forecast demand for aircraft recoverable spares. Box-Jenkins time series analysis was used to analyze and develop forecasting models for ten C-135 recoverable spares.

Two different Box-Jenkins models were developed to forecast demand for each spare. These forecasts were compared to actual demand and to forecasts done using simple exponential smoothing. The first type of Box-Jenkins model built was the multivariate (transfer function) model. In these models, flying hours are the independent/input variable and demand is the dependent/output variable for forecasting. The second type of model is the univariate model in which past demand relationships are used to forecast demand.,

The three types of models forecast one quarter of demand. The results were compared to the actual demand for the quarter. Results showed low correlation between flying hours and demand in the transfer function models. Though each type of model forecasts well, simple exponential smoothing had better results for the short term (three months) forecast. In the majority of forecasts, the three models overestimated demand.